Self-Service Technologies and Enterprise Social Networks – Motivations, User Roles, and Knowledge Contribution

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List of Abbreviations

ATM	Automated Teller Machines
CAGR	Compound Annual Growth Rate
ECIS	European Conference on Information Systems
ESN	Enterprise Social Networks
IBM	International Business Machines Corporation
IS	Information Systems
RO	Research Objective
SAP	Systeme, Anwendungen und Produkte in der Datenverarbeitung
SME	Small and Medium Enterprises
SNA	Social Network Analysis
SST	Self-Service Technologies
USD	US-Dollar

1. Introduction

The first chapter illustrates the subjects, research objectives and research methods covered in this dissertation. At the end, a brief overview of the structure of the dissertation is given.

1.1 Motivation

"The digital revolution has launched a new era of human empowerment and engagement across business, society and in every aspect of our lives. Never before has there been a more powerful influence on human behavior, irrespective of country or culture, than the combined effect of digital technologies. The effects of this shift on society are tremendous," wrote Mervyn Eyre for Forbes in 2017 (Eyre, 2017). She is executive vice president of Fujitsu Americas and has more than 25 years of IT experience. People of the present generation have gotten used to various kinds of digital technologies. Technology-enabled media are used more than ever to interact in the private circle as well as in the business environment. In addition, they changed the way how customers communicate with companies. The result is that people are increasingly independent and at the same time more connected than ever before. In that manner, relationships are shifted from bilateral offline interactions to network oriented digital interactions (Algesheimer and Wangenheim, 2006; Libai et al., 2013). Pervasive connectivity, information abundance, global supply chains, and social media are concepts of people's everyday lives which have brought our society to the new digital era (Bharadwaj et al., 2013). Today, worldwide about 2.6 billion people use social networks such as Facebook, with estimations reaching up to 3 billion users in 2021 (Statista, 2018) which elucidates the immense interconnectedness of people among themselves. In addition, the last couple of years have witnessed a rising level of consumer acceptance of self-service technologies underlining the change in interaction between customers and companies as well as the customers' increasing independence. Taken the example of in-store purchase, people want the fastest checkout process possible, and many are taking matters into their own hands by using checkout kiosks (eMarketer, 2015). Online check-in for flights, mobile ticketing via smartphone, or self-checkout systems in supermarkets are just a few examples that are taken for granted in today's interconnected and fast-paced world (Wang et al., 2013). In addition, the worldwide number of mobile device users has grown to 5.035 billion, with the latest billion users being added in just the last four years (Weiss, 2017). That means that about two-thirds of the world's population now use mobile devices, such as smartphones, tablets or cellphones.

In this new line of research about digital technologies, there is a new field of user, use, and utility research that requires further investigation. The digital users and their usage behavior need to be put at the center of study in order to adapt companies' IT strategies, processes, and systems as well as the management to the new digital age. Standardized services are shifted towards a more dynamic, situation-dependent set of services for digital-oriented people which enables an unprecedented variety of innovations and solutions customized to specific usage scenarios (Brenner et al., 2014).

In particular two new digital technologies change people's behavior and have already found their ways in people's everyday lives: self-service technologies (SST), which change the way how people interact with companies, and enterprise social networks (ESN), which change the way how people interact with each other within companies.

On the one hand, digitalization yielded SST, which alter the interaction between customers and companies and endorse the customers' independence. They are technological interfaces "that enable customers to produce a service independent of direct service employee involvement" (Meuter et al., 2000, p. 50). Compared to personal services, SST are a relatively new service delivery model that changed the nature of the service delivery process in depth (Wang et al., 2013; Meuter et al., 2000). According to a recent report, the global SST market accounted for 15.70 billion USD in 2015 and is expected to reach 37.75 billion USD by 2021 – more than doubling and implying growth at a CAGR of around 15.8% between 2016 and 2021 (Zion Market Research, 2016). Apart from that, the self-checkout market is expected to grow from 2.24 billion USD in 2015 to also double the amount of 4.58 billion USD by 2022 (MarketsandMarkets, 2017). Self-service nowadays is a key aspect of a positive customer experience for the digital users who use their mobile phone to check for instance their account balance while waiting in line at a coffee shop. Due to the increasing prevalence of the "mobile lifestyle" in particular mobile service is gaining popularity lately. Examples thereof are mobile banking or mobile ticketing. This elucidates that self-service is an intrinsic aspect of the age of the customer, where the relationship with the company and the experience they provide is the key to a company's sustaining growth. People nowadays are familiar with the concept of self-service or in the case of retail technology self-checkout and they have come to expect it. In fact, the trend is already continuing. In the beginning of 2018, Amazon opened "Amazon Go", the first checkout-free grocery store. It is designed in that way that shoppers walk into a store and use an app that automatically adds the products they buy to a digital shopping cart. Due to the

"just walk out technology", the costs cumulated in the shopping cart are automatically withdrawn their bank account when leaving the building without waiting in a checkout line. The concept utilizes several technologies to automate the purchase, checkout, and payment steps associated with a retail transaction (Amazon, 2018). This development illustrates the fast developments enabled by digitalization and the progress can be expected to continue.

On the other hand, digitalization yielded ESN which alter people's interconnectedness within companies. ESN are online platforms used in a business context, which facilitate communication, i.e. via messages, and provide functions to find, connect, and interact with colleagues (Aoun and Vatanasakdakul, 2012). With their ability to offer large-scale benefits in enterprise communication, collaboration, knowledge sharing, and thus organizational knowledge management across different silos and departments (Aral et al., 2013; von Krogh, 2012; Kane, 2017), they are gaining rapid adoption (Steinhueser et al., 2015). In 2015, 65% of businesses worldwide had adopted an ESN, as compared to 2006 where merely 10% of the companies were using them (Bughin, 2015). It is forecast that the global market for ESN will grow by a 19% average year-on-year which means the annual revenue will hit 3.5 billion USD by 2019 (Thompson, 2015). The intention behind is to connect social affine employees, so called digital natives and millennials, with their experienced colleagues and thereby improve communication practices as well as business agility through an enhanced employee engagement (Meske and Stieglitz, 2013; Richter et al., 2011). As a matter of fact, ESN can create competitive advantage by favoring effective and efficient business (Riemer et al., 2015; Turban et al., 2011). According to a study by McKinsey, employees spend 20% of their workday searching for information. Yet, ESN can help to reduce knowledge seeking, email volume, and meetings by 25% (Bughin, 2015). ESN solutions are offered by most big players, such as Oracle, SAP, Microsoft, Salesforce, Novell, or IBM. A popular example is the cloud service Yammer, which as of today is used by about 500,000 companies worldwide as well as by 85% of the Fortune 500.[1] In addition, more and more start-ups and newcomers try to join the trend by offering alternatives as no one wants to miss its opportunities.

These powerful trends show that SST and ESN are of great interest for research and practice – and that their importance is likely to keep increasing. For this reason, this dissertation focusses on both subjects within the scope of digital technologies (cf. Figure 1).

[1] https://products.office.com/de-de/yammer/yammer-overview

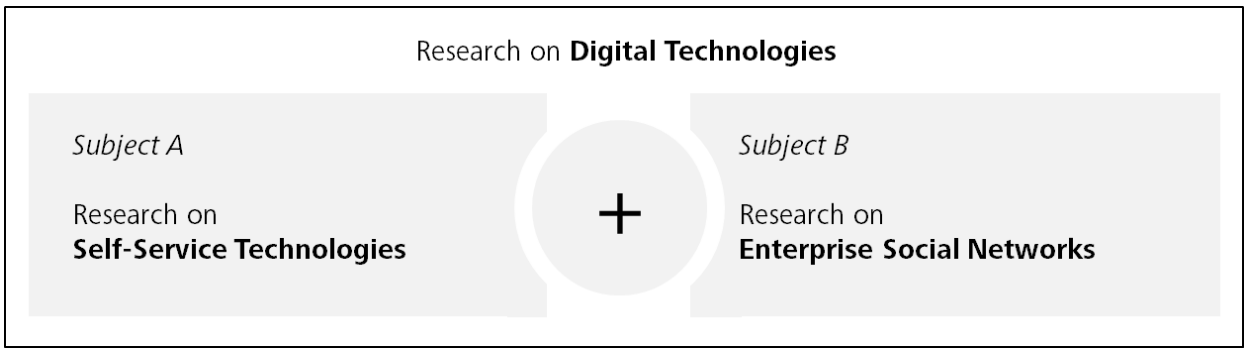

Figure 1: Overview of this dissertation's key subjects

First, this dissertation addresses research on SST (*Subject A*) as they have become an integral part of people's social and economic lives and meanwhile are of undeniable importance for companies (Wang et al., 2013). The business opportunities SST yield for companies can lead to a competitive edge, which is why they have been gaining increasing interest in research lately. In a recent survey, self-checkout rated highest out of a variety of retail technologies on a "customer consciousness scale" with 71% of customers declaring that they are familiar with the concept and 51% even stating that self-checkout is the most useful technology to improve their shopping experience (Miller, 2017). In fact, 40% of customers already prefer self-service over human contact (van Belleghem, 2012). These figures illustrate how deeply SST have penetrated people's lives and transform the ways they interact with companies. While kiosk SST, such as automated teller machines (ATM) in banking or self-checkouts in supermarkets, are already widespread in various industries, mobile service, i.e. mobile banking or ticketing via smartphone, is gaining in popularity and rapidly capturing the markets. The reason is that it offers various benefits for customers, like avoiding queuing or the fact of being independent of opening hours (Kim et al., 2009). But also organizations have recognized the potential of mobile service as it enables companies to collect valuable data on their customers, such as data on usage behavior or data through localization (Grewal et al., 2017; Kleijnen et al., 2005). Thereby, they can gain information on preferences and behavior patterns, which in turn allow for using resources more wisely and making investments more targeted. Hence, SST have gained enormous economic impact and it does not seem surprising that researchers have started to explore why people use them. Extensive research investigated people's utilitarian motivations to use SST, i.e. motivations that "aim to provide instrumental value to the user" (van der Heijden, 2004, p. 695). Examples are time savings, reliability, or increased control over the process (e.g., Alreck and Settle, 2002; Curran and Meuter, 2007; Dabholkar et al., 2003). However, far less research has investigated the hedonic nature of SST. Yet, most human be-

havior is intrinsically pleasure-seeking in nature (Holbrook and Hirschman, 1982) which is why hedonic motivations inevitably need to be considered and further investigated for usage intentions. Research, too, has only begun to investigate motivations leading to adoption (e.g., Curran and Meuter, 2005; Dabholkar and Bagozzi, 2002; Meuter et al., 2005) and rejection of SST (e.g., Kim and Kankanhalli, 2009; Marakas and Hornik, 1996). Albeit, it is still largely unanswered why people switch between different kinds of SST – a promising research field as more and more different kinds of SST are conquering the markets. Against this background, this dissertation focusses on two aspects of SST usage. First, it investigates the motivations to use SST by combining utilitarian and hedonic determinants. Second, the motivations influencing customer's switch from kiosk SST to mobile service are analyzed as to get a more profound understanding of the drivers behind customers' acceptance of SST.

Second, this dissertation aims to contribute to research on ESN (*Subject B*). As noted, ESN bear enormous potential for knowledge management within companies. This has been noticed by organizations and led to an increasing demand to better understand their role and impact on knowledge practices like knowledge sharing, information seeking, or expert finding (Bharadwaj et al., 2013; Herzog et al., 2013). In this line of argument, there is a need to investigate different user roles in ESN usage (Trier and Richter, 2015) to better understand the potential of ESN for knowledge transfer as well as the behavior of its users (Koo et al., 2011), especially with respect to information dissemination (Chau and Xu, 2012), contribution behavior (Zhang and Wang, 2012), and knowledge exchange (Ortbach and Recker, 2014). Nevertheless, social networking behavior in ESN regarding employees' knowledge practices, i.e. how users share and seek knowledge in ESN, is still widely unexplored. Yet, this is especially important with respect to ESN, as users largely differ in terms of their connectivity (e.g. number of friends), their communication activity (e.g. number of messages) as well as their frequency, volume, and quality of user-generated content (Trusov et al., 2010). To date, research has only begun to investigate different users in ESN. For instance, Berger et al. (2014) found that users who add value to the organization by sharing their knowledge in the ESN are amongst the best connected users, and Trier and Richter (2015) identified two interrelated user roles as an explanation for uneven levels of user contributions to ESN. However, it is still largely unanswered how users share and seek knowledge and how user roles can be identified in this line of argument. Moreover, research on user roles to date neglects the relevance of the content for identifying user roles in terms of knowledge exchange. Yet, from a management perspective, it is

essential to know which users outstandingly contribute knowledge, allowing others to benefit from their experience, and how this knowledge is shared. Against this background, this dissertation investigates how users can be classified based on their knowledge exchanging behavior in ESN by proposing different approaches. It considers both – the structural perspective of the users in the network, but also the content perspective, i.e. the knowledge shared within contents – for a more comprehensive understanding of knowledge exchange within companies.

1.2 Research Objectives

The objective of this dissertation is to contribute to research on SST (*Subject A*) and ESN (*Subject B*) for three selected topics (*Topics 1–3*). Subject A covers two topics (*Topic 1: Customers' Motivations to Use Self-Service Technologies;* and *Topic 2: Customers' Motivations to Switch from Kiosk Self-Service to Mobile Service*), while Subject B comprises one topic (*Topic 3: User Roles in Terms of Knowledge Contribution in Enterprise Social Networks)*. Figure 2 provides an overview of these topics as related to this dissertation's subjects. In the following, the topics, and in particular the research objectives of each topic are briefly presented.

Figure 2: Overview of this dissertation's topics

Subject A: Research on Self-Service Technologies

This dissertation addresses two topics related to SST. First, it regards SST from a more general point of view and investigates the customers' motivations to use them. Second, regarding the nature of SST more in depth, it differentiates between different kinds of SST and examines the motivations to switch between them.

- *Topic 1: Customers' Motivations to Use Self-Service Technologies*

SST have become increasingly important for companies. By 2013, worldwide more than 200,000 self-service kiosks in stores existed and their numbers are expected to reach 325,000 by 2021. They enable companies to reduce overhead cost, which elucidates their popularity among vendors. For instance, the cost to process a passenger through an electronic terminal at airport check-ins totals 14 cents as compared to 3 USD which are the expenses with a staffed desk (Hamacher, 2017). Yet, despite the rapid technological change, the fundamentals of superior service are assumed to remain the same. Customers appreciate being recognized, listened to, valued, and cared for – even in times of technological changes (Trend Watching, 2014). However, service employees who used to provide these values to the customers are gradually being replaced by technology-facilitated interactions. Based on this development, it is important to understand why customers are willing to use SST and which motivations drive SST adoption. Prior research has begun to investigate the use and adoption of SST (e.g., Bobbitt and Dabholkar, 2001; Dabholkar and Bagozzi, 2002; Meuter et al., 2005) and researchers argue that the adoption is determined by utilitarian motivations (e.g., Alreck and Settle, 2002; Curran and Meuter, 2007; Dabholkar et al., 2003). However, far less research has investigated the hedonic value of SST and little is known about the hedonic motivations in this context. Yet, it has been shown that the adoption of technology can be better explained when integrating hedonic motivations (e.g., Agarwal and Karahanna, 2000; van der Heijden, 2004; Venkatesh et al., 2012). Against this backdrop, SST can be supposed to be dual technologies with both utilitarian and hedonic value. Thus, most existing research underestimates the importance of hedonic motivations in the context of SST usage. As a result, there is a missing understanding of why customers are willing to use SST considering both – utilitarian as well as hedonic motivations. To address this issue, this dissertation has the following research objective (RO):

RO1: To investigate the utilitarian and hedonic motivations as well as their relative importance for the usage of SST and how a customer's prior experience with SST moderates the influence of the motivations.

- *Topic 2: Customers' Motivations to Switch from Kiosk Self-Service to Mobile Service*

Having analyzed customers' motivations to use SST in general, this dissertation adopts a more in-depth perspective by identifying and investigating motivations that lead to customers' switch between different kinds of SST. SST can be differentiated based on the technology used, namely interactive kiosk, internet (including mobile), and interactive

voice response (Meuter et al., 2000) whereas the internet-based SST type is the most common (Evanschitzky et al., 2004; Yen and Gwinner, 2003). Lately, in particular mobile service has been gaining popularity among customers as well as among companies. The number of people checking their bank accounts on a smartphone increased from 28% in 2014 to 44% in 2016. People are also more comfortable with paying bills via mobile banking — 29% in 2016 as compared to 20% in 2014 (MobileEcosystemForum, 2017). Thereby, they reveal sensitive data such as personal information or behavior patterns. Against this background, companies endorse their customers to switch from "anonymous" SST, such as kiosks (e.g., banking via ATM), to mobile service (e.g., mobile banking via smartphone) as mobile service offers companies the opportunity to collect this valuable data on their customers' usage behavior as compared to kiosk SST where customers act anonymously. In the latter case, they for instance do not necessarily reveal sensitive personal data when buying a train ticket. However, not all customers switch from kiosk SST to mobile service. While prior research has begun to investigate the reasons for SST adoption (e.g., Curran and Meuter, 2005; Dabholkar and Bagozzi, 2002; Meuter et al., 2005), to date only little research has investigated the reasons for SST rejection and no research has investigated the reasons for switching between SST. Yet, research on technologies explained that users' resistance behavior prevents users from switching between technologies (Laumer et al., 2016). That implies that users are locked into a status quo and therefore do not switch to alternatives (Polites and Karahanna, 2012). This elucidates the importance for companies to better understand the motivations behind customers' switch in order to deploy companies' resources wisely. In other contexts, monetary incentives have been identified as effective motivators to influence people's behavior (Albers et al., 2013) which is why they may constitute attractive means for companies to convince their customers of mobile service usage. Yet, to date no research has considered this potential and analyzed different kinds of monetary incentives in this context. Consequently, although positive and negative motivations leading to adoption and rejection of SST have been explored, existing research still lacks an in-depth understanding of the motivations influencing the switch from kiosk SST to mobile service. Against this background, this dissertation pursues two research objectives:

RO2: To investigate positive and negative motivations as well as their relative importance for the switch from kiosk SST to mobile service.

RO3: To investigate the role of different kinds of monetary incentives and their relative importance for convincing customers to switch to mobile service.

Subject B: Research on Enterprise Social Networks

This dissertation expands research on ESN by proposing and evaluating novel methodological approaches to classify users and identify user roles in terms of knowledge contribution in ESN.

- *Topic 3: User Roles in Terms of Knowledge Contribution in Enterprise Social Networks*

  As noted, ever more companies use ESN for knowledge management. However, there is still a lack of understanding of users' knowledge exchanging behavior. This is why there is an increasing demand to better understand the role and impact of this social technology in and on knowledge-intensive corporate work (Bharadwaj et al., 2013; Herzog et al., 2013; Richter et al., 2013). Research further demands for investigating the behavior of users in ESN (Koo et al., 2011; Kuegler and Smolnik, 2014), especially with respect to knowledge sharing and seeking in ESN (Ortbach and Recker, 2014; Recker and Lekse, 2015) as well as different user roles in ESN usage (Trier and Richter, 2015).

  Sharing and demanding with others is deeply rooted in human nature. Every time individuals interact with others, they have to decide within the two extremes of whether to claim as much value as possible or contribute value without expecting anything in return (Grant, 2013). Over the past decades, social scientists have discovered that people differ tremendously in their preferences for reciprocity – their desired mix of giving and taking. On a related note, social network theory implies that not all nodes in a social network can be considered as equal. They largely differ in terms of their connectivity, communication behavior, as well as frequency, volume, and quality of user-generated content (Trusov et al., 2010). In this regard, it is essential to know which users share their knowledge in the ESN and thus help others to get their work better done. However, social networking behavior in ESN with respect to employees' knowledge practices, i.e. how users share and seek knowledge in ESN, is still widely unexplored. Here, more specifically, users' reciprocities in terms of giving and taking knowledge within an ESN and their structural characteristics have not yet been subject of academic discussion. Moreover, identifying user roles based on the contents exchanged in an ESN has not been addressed, either. Yet, this perspective bears huge potential as about 80% of an organization's information is contained within

text documents (Tan, 1999) and there are calls to deepen the understanding of these potentials (e.g., Beck et al., 2014; Cetto et al., 2016).

In order to address these issues, this dissertation aims to investigate the knowledge exchanging behavior of users in ESN by proposing different approaches for classifying users with respect to their amount of sharing and seeking knowledge. Moreover, the structural characteristics of these different user roles are investigated in depth. Against this background, this dissertation pursues two research objectives:

RO4: To propose novel methods to classify users and identify user roles with respect to their amount of sharing and seeking knowledge in ESN based on a Social Network Analysis approach and to analyze the structural characteristics of the user roles.

RO5: To propose a new methodological approach to classify users and identify user roles based on their knowledge contribution in contents, in particular in messages, and to analyze the structural characteristics of the user roles.

All of these research objectives are addressed in five papers (cf. Table 1).

Paper	Title	Corresponding subject	Corresponding topic (RO)	Authors	Status	Journal/Conference	VHB-Rank
1	*Why Should I Do it Myself? – Hedonic and Utilitarian Motivations of Customers' Intention to Use Self-Service Technologies*	*Subject A*	*Topic I (RO1)*	A. Cetto, J. Klier, M. Klier	Published	Proceedings of the European Conference on Information Systems (ECIS)	B
2	*Customers' Intention to Switch to Mobile Self-Service Technologies*	*Subject A*	*Topic 2 (RO2)*	P. Bedué, A. Cetto, J. Klier, M. Klier	Published	Proceedings of the European Conference on Information Systems (ECIS)	B
3	*Can Money Convince You? – Monetary Incentives and Mobile Self-Service Technologies*	*Subject A*	*Topic 2 (RO3)*	A. Cetto	Under Review	Proceedings of the Internationale Tagung Wirtschaftsinformatik (WI)	C
4	*The Blessing of Giving: Knowledge Sharing and Knowledge Seeking in Enterprise Social Networks*	*Subject B*	*Topic 3 (RO4)*	A. Cetto, J. Klier, M. Klier, A. Richter, K. Wiesneth	Published	Proceedings of the European Conference on Information Systems (ECIS)	B
5	*"Thanks for sharing" – Identifying Users' Roles based on Knowledge Contribution in Enterprise Social Networks*	*Subject B*	*Topic 3 (RO5)*	A. Cetto, M. Klier, A. Richter, J. Zolitschka	Published	Computer Networks	n/a (Journal Impact Factor: 2.52)

Table 1: Overview of this dissertation's papers

1.3 Research Methods

According to Hevner et al. (2004) two paradigms characterize much of the research on information systems (IS): behavioral science and design science. The design science paradigm is rooted in engineering disciplines and is a relative young discipline. It seeks to create innovations and IT artefacts, such as constructs (vocabulary and symbols), **methods** (algorithms and practices), **models** (abstractions and representations) as well as instantiations (implemented and prototype systems), and aims at utility (Hevner et al., 2004; Peffers et al., 2007; March and Smith, 1995). Behavioral science has its roots in natural science research methods with a longer history and seeks to develop and justify theories explaining human phenomena, i.e. **preferences and behavior of individuals** or organizations involved with IS. Against this background, its goal is the truth. Often, the object of study in behavioral science IS research is an IT artifact, implemented in an organizational context. Theories predominantly predict or explain phenomena that occur regarding the artifact's use (intention to use), perceived usefulness, and impact on individuals and organizations (net benefits) depending on system, service, and information quality (DeLone and McLean, 1992, 2003; Seddon, 1997). For behavioral science IS research, statistical significance is established as a clear and common measure of its results' rigor. As the aim of design science IS research is the construction of improved IS-related problem solutions, it uses utility for practice as a clear and common measure of its results' relevance (Winter, 2008).

Although both research paradigms show a distinct orientation, one focusing on behavior and one generally on IT artifacts, they complement each other (Hevner et al., 2004). While the goal of design science is utility in form of an effective artifact, the goal of behavioral science is truth, such as a justified theory. Truth can lead to the design of new artifacts, while utility leads to new theories (Hevner et al., 2004). As SST and ESN are relatively new phenomena, the behavioral science approach is initially needed to better understand their role and impact as well as their users' behavior. On this basis, implications and guidance are derived based on the developed and justified theories. Therefore, this dissertation mainly follows the behavioral science approach, especially in regard of SST (cf. Papers 1 - 3). Yet, for the proposition of novel methodological approaches for user classifications in ESN, additionally the design science approach is applied (cf. Papers 4 - 5). In the following, an overview of each paper's research para-

digm, its respective research approach as well as the paper's implications is briefly presented (cf. Table 2 for an overview).

- *Paper 1: Why Should I Do it Myself? – Hedonic and Utilitarian Motivations of Customers' Intention to Use Self-Service Technologies*

  Paper 1 follows the behavioral science paradigm (Hevner et al., 2004; Wilde and Hess, 2007) to explore how utilitarian and hedonic motivations influence customers' intention to use SST. For this purpose, specific utilitarian and hedonic motivations are proposed for the particular context of SST to get a deep understanding of the motivations behind customers' usage as well as of other factors moderating the influences of these motivations. For the investigation, a case study is conducted as it allows the exploration and understanding of complex issues and can be considered a robust research method particularly when a holistic, in-depth investigation is required (Yin, 2009; Dubé and Paré, 2003). The design of the case study follows the approach of Yin (2013). For the case study, a German IKEA store is selected as it has already introduced SST in terms of self-service kiosks in Germany some years ago thus enabling to gain data from customers with different experience levels (Kim and Gupta, 2009; van der Heijden et al., 2003). That way, it can be reverted to a big and diverse group of customers. The data of 433 customers are collected in a survey which deliver the basis to investigate established hypotheses. The analysis is based on Structural Equation Modeling techniques (cf. Bollen and Long, 1992). The results of the study shed light in the motivations driving user behavior in terms of SST and thereby, serve as a basis for further research on the important aspect of the hedonic value of SST in particular. They help practice to increase the usage rate of SST by taking effective means to address people rarely using SST so far. As the prevalence of SST has been increasing with unpredicted speed and scope during the last years and must be expected to increase even further, it is inevitable for both, theory and practice, to get a better understanding of users' behavior regarding this relatively new technology and especially the motivations driving this behavior.

- *Paper 2: Customers' Intention to Switch to Mobile Self-Service Technologies*[2]

[2] Please note that in Paper 2 and Paper 3 mobile service is named mobile SST due to consistency reasons. Yet, its meaning is the same and it does not change the results.

To explore the motivations behind customers' switch between different kinds of SST, Paper 2 also follows the behavioral science paradigm (Hevner et al., 2004; Wilde and Hess, 2007). The study focusses on the switch from kiosk self-service to mobile service as these represent SST with different degrees of anonymity. While customers reveal sensitive data when using mobile service, such as information on their usage behavior, personal information or geographic positions, customers act anonymously when using kiosk SST as they do not necessarily reveal the aforementioned data. Against this backdrop, companies endorse their customers to switch to mobile service with the aim to collect valuable customer data. Therefore, Paper 2 investigates positive and negative motivations influencing the intention to switch from kiosk SST to mobile service based on a case study (Yin, 2013). Moreover, the relative importance of the motivations for the switch are investigated based on Structural Equation Modeling techniques (cf. Bollen and Long, 1992). For data collection, a field survey methodology is adopted. As public transportation in Germany offers different well-accepted SST options, among them kiosk SST and mobile service, a survey at railway stations is considered an effective method for capturing the proposed motivations as well as their impact on the switch. In the case study (Yin, 2013), the data of 315 customers are collected. To analyze the hypotheses, a two-step approach is utilized to ensure reliability and validity of the measures before examination of the structural model parameters (cf. Anderson and Gerbing, 1988). The findings may serve as a basis for further research on the versatile nature of different kinds of SST. As this versatile nature is ever more prevalent and people take an increasing variety of SST options for granted, it is an essential area of interest for both theory and practice. With more and more companies introducing not only one but rather different kinds of SST and with the additional prospect that in the foreseeable future even more SST options must be expected to conquer the markets, it is crucial for companies to gain an in-depth understanding of the motivations behind customers' acceptance of new kinds of SST to ensure profitable market launches. This is why understanding the main driving motivations leading to an actual switch between SST is crucial for companies' economic long-term survival.

- *Paper 3: Can Money Convince You? – Monetary Incentives and Mobile Self-Service Technologies*

Based on the behavioral science paradigm, Paper 3 examines the role of different kinds of monetary incentives for customers' switch to mobile service. Since only limited research

has been conducted in this research area so far, following Yin (2013), this dissertation draws on an exploratory case study research, allowing to explore any phenomenon in the data which serves as a point of interest to the researcher. The purpose is to open up the door for further examination of the phenomenon observed (McDonough and McDonough, 2014; Yin, 2009). Against this backdrop, monetary incentives that may be relevant in the context of mobile service are identified thoroughly (after researching a multitude of monetary incentives deriving from various contexts) and investigated: cash payments to customers, vouchers to purchase specific goods or services, price discounts, loyalty programs including reward points, and special offers only available via mobile service. A case study at German train stations is conducted to get a deeper understanding of the relative importance of the individual monetary incentives for convincing customers to use mobile service. The design of the case study follows the approach of Yin (2013). For data collection, a field survey methodology is conducted, allowing to collect 346 usable responses. The data is analyzed using statistical tests as this has been found suitable for ordinal data, such as data deriving from Likert scales, and sufficiently robust to bear largely unbiased answers that are acceptably close to "the truth" (Norman, 2010). Against this background, they constitute valid instruments for this study that can shed valuable first insights in the role of monetary incentives in the context of mobile service. The findings promote an improved understanding of the opportunities monetary incentives offer in the context of mobile service – an emerging research area that is increasingly gaining interest for research and practice. In this way, companies are supported to understand which monetary incentives need to be invested on in order to increase adoption of their mobile service and thus, reach profitable usage rates. As indicated above, as even more SST options must be expected to enter the markets, it is crucial for companies to know not only why customers use new kinds of SST but also how to convince their customers of using them. This study can lay the foundation for further research on this emerging research area.

- *Paper 4: The Blessing of Giving: Knowledge Sharing and Knowledge Seeking in Enterprise Social Networks*

  The design science paradigm (Hevner et al., 2004) is followed to propose two novel methods to identify user roles in ESN based on their knowledge exchanging behavior. Using a Social Network Analysis (SNA) approach (Wasserman and Faust, 2009), users are classified with respect to their amount of sharing and seeking knowledge in an ESN. According to

Freeman (2000, p. 350), SNA "involves theorizing, model building, and empirical research focused on uncovering the patterning of links among actors" by, for instance, quantifying the centrality of nodes within a network. In so doing, two aspects for characterizing the user roles are considered: knowledge sharing and seeking behavior in a knowledge base (i.e. wiki) as well as communication activities and connectedness between users. Against this backdrop, the "Absolute Distance Measure" and the "Relative Distance Measure" are proposed to identify user roles in ESN based on their knowledge exchanging behavior. To ensure the significance and validity of the different approaches, the Bowker-Test (Bowker, 1948) is used. Further, the users of the user roles are investigated in terms of structural characteristics as well as their positions in the organizational hierarchy. Using the behavioral science paradigm, the research objective is approached with the case of the medical service unit of the German Armed Forces (Deutsche Bundeswehr). They launched an ESN that fosters the knowledge transfer by including a knowledge base to which employees contribute publically available (scientific) content. The medical service unit is distributed amongst five major military hospitals in Germany, 37 German universities offering medical studies, and 200 other facilities. Hence, the analysis is enabled by a plethora of data generated when users interact and connect with others (Giles, 2012). As this study proposes two novel methods to distinguish between users based on their knowledge exchange, it helps companies to identify the users of the network that can spread knowledge within the company in the best way. This supports the effective distribution of information in an ESN and ultimately improves the knowledge management of the company. While this study is a first but indispensable step with regard to studying users' knowledge exchanging behavior in ESN, it builds a profound basis for further research on the characteristics of those users that are crucial to improve a company's knowledge management.

- *Paper 5: "Thanks for sharing" – Identifying Users' Roles based on Knowledge Contribution in Enterprise Social Networks*

  The research objective of Paper 5 is addressed using a mixed methods research approach. Mixed methods research is the combination of qualitative and quantitative methods. As the usage of only one method would not be able to capture all circumstances adequately, the results of multiple methods are compared and interpreted to allow a comprehensive view on the respective research objectives (Ågerfalk, 2013). Using quantitative methods, a new methodological approach for user classification is proposed based on users' knowledge con-

tribution in ESN contents, following the design science paradigm. A text analysis approach (Dumais et al., 1998; Feldman and Sanger, 2007; Li and Wu, 2010) allows to classify messages and identify user roles depending on their knowledge sharing and seeking behavior in those messages, i.e. their knowledge contribution in the ESN. In addition, the structural characteristics of the user roles are analyzed via SNA (Wasserman and Faust, 2009) and further activities in the network as well as the content patterns and characteristics of the messages written by each user role are investigated. Finally, using a qualitative methods approach, the results are triangulated on behalf of user interviews (Richter and Riemer, 2013), following the behavioral science paradigm. The approach is applied to a large volume of ESN communication data from a large multinational consulting company employing more than 180,000 people in 40 countries worldwide and using the ESN Yammer. The case organization is selected as it delivers vast amounts of data from 110,910 messages posted inside the ESN during the time period, written by 9,806 users, which enables a sound data analysis. The findings shed light on employees' knowledge contribution in ESN from the content perspective, thus complementing and rounding out user classifications from the structural perspective. As companies aim at becoming acquainted with the characteristics of their ESN users to ensure an efficient knowledge management in the company, the findings of this study well help to attain this aim by offering valuable in-depth insights in the knowledge contribution behavior of ESN users.

Topic	Paper	Research Paradigm	Research Approach	Data
Topic I	Paper 1 *Why Should I Do it Myself? – Hedonic and Utilitarian Motivations of Customers' Intention to Use Self-Service Technologies*	Behavioral science	The effects of hedonic and utilitarian motivations on the usage of self-service technologies are investigated based on a case study using structural equation modelling	Survey data
Topic II	Paper 2 *Customers' Intention to Switch to Mobile Self-Service Technologies*	Behavioral science	The effects of positive and negative motivations on the switch from kiosk SST to mobile service are investigated based on a case study using structural equation modelling	Survey data
	Paper 3 *Can Money Convince You? – Monetary Incentives and Mobile Self-Service Technologies*	Behavioral science	First insights on different kinds of monetary incentives in the context of mobile service are delivered based on a case study using statistical tests	Survey data
Topic III	Paper 4 *The Blessing of Giving: Knowledge Sharing and Knowledge Seeking in Enterprise Social Networks*	Behavioral science and design science	Two methods for user classification based on the knowledge contribution in ESN are developed, evaluated, and the users' characteristics are investigated based on a case study using SNA and statistical tests	Company owned log files
	Paper 5 *"Thanks for sharing" – Identifying Users' Roles based on Knowledge Contribution in Enterprise Social Networks*	Behavioral science and design science	A methodological approach for user classification based on the knowledge contribution in ESN messages is developed, evaluated, and the users' characteristics are investigated based on a case study using a text analysis approach and SNA	Company owned data and interviews

Table 2: Overview of this dissertation's research paradigm, research approach and data

1.4 Structure of the Dissertation

The dissertation is structured as follows (cf. Figure 3): in this introduction, the dissertation is motivated and a brief overview over its research objectives and methods is given. Afterwards, the individual papers of this dissertation are presented. The papers addressing SST *(Subject A; Topics 1 and 2)* are presented in Chapter 2, while the papers addressing ESN *(Subject B; Topic 3)* are presented in Chapter 3. The dissertation ends with a brief conclusion in Chapter 4 including its major findings as well as a discussion on its limitations and outlooks.

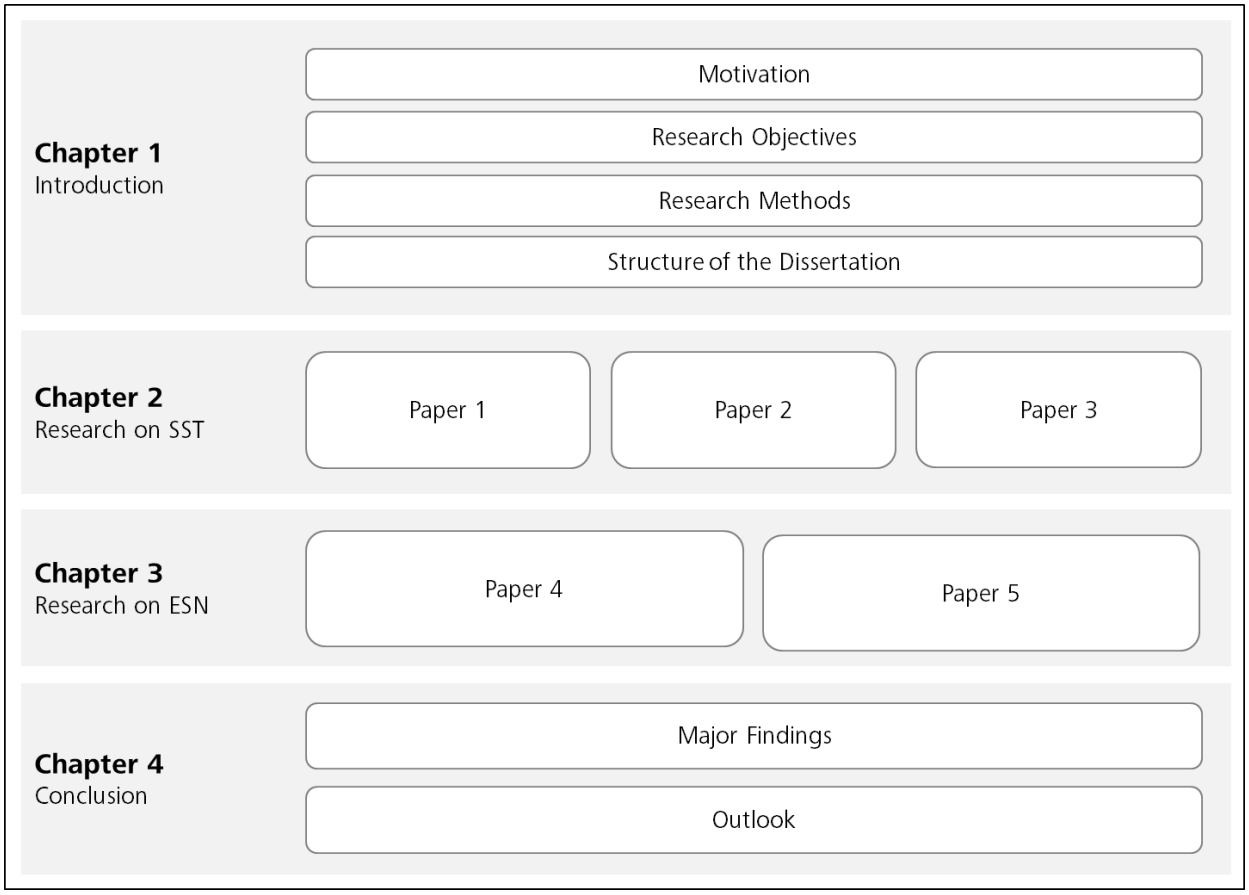

Figure 3: Overview of the structure of the dissertation

2. Research on Self-Service Technologies

2.1 Paper 1: Why Should I Do it Myself? – Hedonic and Utilitarian Motivations of Customers' Intention to Use Self-Service Technologies

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WHY SHOULD I DO IT MYSELF? HEDONIC AND UTILITARIAN MOTIVATIONS OF CUSTOMERS' INTENTION TO USE SELF-SERVICE TECHNOLOGIES

Complete Research

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Abstract

Customer self-service technologies (SST) have been gaining increasing economic importance given their proliferation in the customer service industry. Self-service kiosks have gradually been replacing traditional service employees and their progress is expected to continue. The growing relevance of SST results in the need for companies to understand why customers are willing to use SST and which motivations drive SST adoption. Two central constructs determine a customer's willingness to use SST, namely utilitarian and hedonic value. Thus, the aim of this paper is twofold: first, we explore the multidimensional nature of utilitarian and especially hedonic value. Second, we examine their relative importance in determining repeat use intention, depending on a customer's prior experience with SST. We develop a research model based on means-end chain (MEC) theory. The results underline that both values positively influence repeat use intention of SST. While hedonic value is prevalent for customers with little experience, utilitarian value weights stronger for customers with more experience.

Keywords: Self-service technology, Repeat use intention, Utilitarian value, Hedonic value.

1 Introduction

Self-service technologies (SST) have become increasingly important within the customer service industry. The amount spent on technology-based self-service solutions was estimated to exceed $5.8 bn in 2013 (Dabholkar and Spaid, 2012). For North America, self-service kiosk transactions are predicted to have surpassed one trillion dollars by the end of 2014 (Giebelhausen et al., 2014). Despite the rapid technological change, the fundamentals of superior service remain the same. Customers appreciate being recognized, listened to, valued and cared for – even in times of technological changes (Trend Watching, 2014). However, service employees who used to provide these values to the customers are gradually replaced by technology-facilitated interactions. Automated teller machines in banking, self-checkout systems in supermarkets, and services over the internet such as online check-in for flights have become an integral part of today's fast-paced world (Wang et al., 2013). Due to the rapid evolution of technology, the development of SST is expected to proceed and become an integral part of service delivery (Beatson et al., 2007). Based on this development, it is important to understand why customers are willing to use SST and which motivations drive SST adoption.

Prior research has begun to investigate the use and adoption of SST in firm-customer interactions (Bobbit and Dabholkar, 2001; Curran and Meuter, 2007; Dabholkar and Bagozzi, 2002; Lee et al., 2012; Meuter et al., 2000; Meuter et al., 2005). Researchers argue that the adoption of technology in general is determined by utilitarian influence factors like Perceived Usefulness and Perceived Ease of Use based on the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh and Bala, 2008). Additionally, it has been shown that the adoption of technology can be better explained when integrat-

ing hedonic influence factors like Perceived Enjoyment (Agarwal and Karahanna, 2000; Dabholkar, 1996; van der Heijden, 2004; Venkatesh., 2000; Venkatesh et al., 2012). For using SST, research has already explored utilitarian motivations such as time savings, reliability, and increased control (Alreck and Settle, 2002; Curran and Meuter, 2007; Dabholkar, 1996; Dabholkar et al., 2003; Davis et al., 1989; Meuter et al., 2000). However, far less research has investigated the hedonic nature of SST and little is known about the composition of hedonic value. Combining both views, we believe that SST are dual technologies with both utilitarian and hedonic motivations. Additionally, prior studies in other contexts have shown that the factors that motivate initial or repeat purchase intention are quite different, depending on prior experience (e.g., initial purchase vs. repeat purchase) (Cheung et al., 2003; Kim and Gupta, 2009; Parasuraman, 1997; van der Heijden et al., 2003). Hence, we assume that utilitarian and hedonic motivations to use SST vary with customers' prior experience with SST.

To improve our understanding, this paper develops a new model to explore why customers are willing not only to use SST but rather to reuse SST. More specifically, as the reasons for reuse intention of SST vary from other technologies, we examine the unique composition and thus the multidimensional nature of utilitarian and especially hedonic value and their relative importance in determining repeat use intention of SST. Thereby, we provide further insights into what differentiates SST from other technologies. Moreover, we analyse how a customer's prior experience with SST moderates the influence of the values on repeat use intention and therefore gain an understanding of the differences between different customer groups with specific experience levels. The research questions driving this study are: 1) *What are the benefits of utilitarian and especially of hedonic value for using SST?* 2) *Do customer motivations for using SST differ with varying customer SST experience?* To investigate these questions we build upon means-end chain (MEC) theory (Gutman, 1997) which states that customers obtain their values (ends) through positive consequences or benefits deriving from the attributes (means) of an act. The study helps us to gain a better understanding of how the importance of utilitarian and hedonic value differs for a customer's repeat use intention of SST.

The remainder of the paper is organised as follows: In Section 2, we review the theoretical foundations and related literature. The description of the research model in Section 3 is followed by the research methodology and the results in Section 4. Afterwards, we discuss theoretical and practical implications in Section 5. In Section 6, we conclude with a brief summary of our research.

2 Theoretical Background

SST are technological interfaces "that enable customers to produce a service independent of direct service employee involvement" (Meuter et al., 2000, p. 50). Compared to personal services, SST constitute a relatively new service delivery model (Beatson et al., 2007) that has changed the nature of the service delivery process in depth (Wang et al., 2013; Meuter et al., 2000). As Yan et al. (2013) point out, most research on SST focuses on either 1) the outcomes of SST adoption (e.g., Weijters et al., 2007), 2) the determinants of SST adoption (e.g., Curran and Meuter, 2007; Venkatesh et al., 2012), or 3) the benefits of and reasons for SST adoption (e.g., Bitner et al. 2002; Meuter et al., 2000). Studies in these fields which are important for our research questions are summarized below. Furthermore, we illustrate the foundation of MEC theory (Gutman, 1997) which serves as basis for our research model.

2.1 Adoption theory and outcomes of self-service technology adoption

User acceptance has been seen as the most important factor in determining the success or failure of any information system project (Davis, 1993). User acceptance can be defined as "the demonstrable willingness within a user group to employ information technology for the tasks it is designed to support" (Dillon and Morris, 1996, p. 3). It was conceptualized as an outcome variable in a psychological process when users make decisions about technology (Dillon and Morris, 1996). To predict information technology acceptance, the most prevalent model is Davis' (1989) TAM. TAM is derived from the Theory of Reasoned Action which states that beliefs influence intentions, and intentions influence one's actions (Ajzen and Fishbein, 1975). Thus, TAM builds a causal chain "linking external variables

to […] actual use" (Davis and Venkatesh, 1996, p. 20). In that context, researchers have shown that the intention to use is the strongest predictor of actual use (Davis et al., 1989; Taylor and Todd, 1995).

Against this background, intention to use and repeat use intention have been commonly used as an outcome variable in the context of SST adoption (Curran and Meuter, 2005; Lee et al., 2012; Meuter et al., 2005; Venkatesh et al., 2012). In our research we use the outcome variable repeat use intention that reflects the subjective probability that a customer will continue to use SST from the same company. Compared with potential customers, "repeat (i.e. experienced) customers are better at comprehending and evaluating the information and attributes" of SST due to their experience (Chiu et al., 2012, p. 5).

2.2 Determinants of repeat use intention of self-service technologies

Human motivations, cognitive (utilitarian) as well as affective (hedonic), are aimed primarily at individual gratification and satisfaction (McGuire, 1974), which provides the theoretical basis for explaining why people engage in SST. Previous research mainly focuses on the utilitarian aspects of SST usage, described as task-related values such as time savings or reliability (Bitner et al., 2002; Dabholkar, 1996; Dabholkar et al., 2003; Hoffman and Novak, 1996; Meuter et al., 2000) that "aim to provide instrumental value to the user" (van der Heijden, 2004, p. 695). Utility is thus considered as "the potential rewards or punishments that an individual may expect from engaging in a given behaviour" (Curran and Meuter, 2007, p. 285). Lee et al. (2012) for example assert that compared to the traditional counter, SST enable customers to save time. Dabholkar et al. (2003) state that people prefer SST because they give them control and are reliable and easy to use.

However, traditional utilitarian explanations ignoring hedonic value are insufficient to reflect the reasons for SST usage (Curran and Meuter, 2007). Most people are intrinsically pleasure-seeking in nature (Holbrook and Hirschman, 1982). In contrast to utilitarian value, hedonic value grounds in the "aim to provide self-fulfilling value to the user" (van der Heijden, 2004, p. 696). Based on this reasoning, the initial TAM (utilitarian-oriented) was extended to include a new construct called Perceived Enjoyment to take into account the fun factor of using a technology (van der Heijden, 2004; Venkatesh and Bala, 2008). Also in the context of SST, customers typically desire to obtain a feeling of pleasure (Dabholkar et al., 2003). Dabholkar (1996) for example states that customers are more likely to use SST if it looks like being fun (Dabholkar, 1996). Curran and Meuter (2007) found that fun is even more important than utility for influencing the adoption of SST (Curran and Meuter, 2007). Dabholkar and Bagozzi (2002) suggest that people are more attracted by SST if their usage is enjoyable.

We believe that both views should be combined and postulate that SST are dual technologies that are both hedonic- and utilitarian-oriented. Thus, both values have to be considered as key determinants in understanding the customers' repeat use intention of SST. Accordingly, this study adopts a two-dimensional conceptualisation of customer value.

2.3 Benefits of self-service technology adoption

2.3.1 Utilitarian benefits of using self-service technologies

The reasons why customers adopt SST "depend upon the benefits they can receive from SST usage" (Yan et al., 2013, p. 3). Reflecting the literature, the most important utilitarian benefits of using SST include time savings (Dabholkar, 1996), control (Bateson, 1985), reliability (Davis et al., 1989), ease of use (Lee et al., 2012), and avoidance of service employees (Meuter et al., 2000).

First, SST can allow for the actual transaction to be performed more quickly than by a service employee, thus leading to time savings for the customer (Dabholkar, 1996; Dabholkar et al., 2003). Advantages in this category include shorter waiting time as well as less time taken for the actual service delivery (Dabholkar, 1996). A further benefit of using SST is the user's feeling of being in control of the process of service delivery when being responsible for the service him- or herself (Bateson, 1985; Dabholkar, 1996; Dabholkar et al., 2003; Sarel and Marmorstein, 2003). In addition, for technologies it is particularly important to prove their reliability to the customer to reduce the feeling of uncertainty

(Walker et al., 2002). Reliability refers to how accurately the orders will be fulfilled by SST (Dabholkar, 1996). Naturally, a customer is more likely to use SST if they work properly. Due to technological accuracy, SST are perceived as preventing mistakes a service employee might make, such as charging a wrong price (Dabholkar, 1996; Dabholkar et al., 2003). Beyond these benefits, the effort to use the technology and the complexity of the process of service delivery are of crucial importance for the decision. These two criteria – effort and complexity – are related and comprised in the concept ease of use (Dabholkar, 1996), which is important for customers' adoption of SST (Davis, 1989; Dabholkar and Bagozzi, 2002; Dabholkar et al., 2003; Lee et al., 2012; Meuter et al., 2000). Avoiding interactions with the service employee which may be inevitable at the traditional service counter is also seen as a benefit (Dabholkar, 1996; Dabholkar and Bagozzi, 2002; Lee et al., 2012; Meuter et al., 2000).

Utilitarian benefits of SST	References
Time Savings	Alreck and Settle (2002), Dabholkar (1996), Dabholkar et al. (2003), Lee et al. (2012); Meuter et al. (2000)
Control	Bateson (1985), Dabholkar (1996), Dabholkar et al. (2003), Hoffman and Novak (1996), Sarel and Marmorstein (2003)
Reliability	Dabholkar (1996), Dabholkar et al. (2003), Davis et al. (1989), Weijters et al. (2007), Yan et al. (2013)
Ease of Use	Dabholkar and Bagozzi (2002), Dabholkar et al. (2003), Meuter et al. (2000), Lee et al. (2012), Weijters et al. (2007)
Avoidance of Service Employee	Bateson (1985), Dabholkar (1996), Dabholkar and Bagozzi (2002), Langeard et al. (1981), Lee et al. (2012), Meuter et al. (2000)

Table 1. Utilitarian benefits of using SST.

2.3.2 Hedonic benefits of using self-service technologies

Researchers suggest that future work on SST adoption should particularly address hedonic reasons (Bagozzi, 2007; van der Heijden, 2004; Venkatesh, 2000). Dabholkar (1996) states that customers are more likely to use SST if they look like being fun. This enjoyment is referred to as "the feeling arising intrinsically from interacting with […] or from the novelty aspect" of a technology (Dabholkar, 1996, p. 35). Langeard et al. (1981) found that people who enjoy playing with machines prefer self-service options. Thus, the benefit enjoyment is important to customers when evaluating technological options, such as SST. Closely related to the enjoyment aspect is the novelty seeking aspect of a technology which encourages customers to try new things. Novelty seeking is referred to as "the desire to seek out new stimuli" (Hirschman, 1980, p. 284). Agarwar and Karahanna (2000) analysed the customer's personal innovativeness and showed that it has a positive influence on the attitudes toward and intention to use technological products. Accordingly, customers with a higher inclination toward novelty seeking are more willing to use technology-based products, such as SST, have a stronger intrinsic motivation to use them, and enjoy the stimulation of trying new ways to approach old problems (Dabholkar and Bagozzi, 2002; Hirschman, 1980; Parasuraman, 2000). Another hedonic benefit closely related to enjoyment is the feeling of being challenged (Ghani, 1991; Koufaris, 2002; Novak et al., 2000). The challenges presented by an activity are among the most important predictors of flow (Novak et al., 2000). The concept of flow was introduced by Csikszentmihalyi (1975) to "understand enjoyment […] as ongoing process which provides rewarding experiences in the present" (Csikszentmihalyi, 1975, p. 9) and is referred to as "a cognitive state" (Novak et al., p. 24) derived from "activities which are enjoyable themselves" (Csikszentmihalyi, 1975, p. 2). Using a technology such as SST properly can be a challenge in such a way that the customer may perceive it as a demanding experience to go through the process without failure. Comparable with a game, a feeling of satisfaction arises if he or she succeeds in doing so (Koufaris, 2002). This positive technology experience affects both customer responses and the intention to return in the future positively (Koufaris, 2002).

Hedonic benefits	References
Enjoyment	Dabholkar (1996), Davis et al. (1992), Langeard et al. (1981)
Inherent Novelty Seeking	Agarwar and Karahanna (2000), Dabholkar and Bagozzi (2002), Hirschman (1980), Parasuraman (2000)
Challenges	Ghani et al. (1991), Koufaris (2002), Novak et al. (2000)

Table 2. Hedonic benefits of using technologies.

2.4 Means-end chain (MEC) theory

According to MEC theory (Gutman, 1997), customers think about products and services in terms of attributes. Attributes are the means through which the desired (positive) consequences and values (ends) may be achieved. As positive feelings only derive from benefits, the desired outcomes can be set equal with benefits (Woodside, 2004). Based on MEC theory, customers choose actions that avoid undesired and produce desired consequences. Once they have learned which acts produce the desired consequences (benefits) and values, they adapt their choice behaviour accordingly (Gutman, 1997). In other words, customers do not use services and products because of their attributes, but because of their values and benefits. MEC theory describes a hierarchy of goals: attributes are the lowest level, leading to the second level, the benefits, which then lead to the goals or values, which motivate customers to engage in a certain choice behaviour. Moreover, MEC theory says that customer behaviour is value driven, which means that the customers' choice patterns are, ultimately, influenced by the perceived values (Gutman, 1997). Accordingly, in the case of SST, utilitarian and hedonic benefits are the sub-goals which lead to the higher goals or utilitarian and hedonic values, with these higher goals being the final goals that trigger repeat use intention. MEC theory does not explicitly link value to behavioural intention, but a number of empirical studies have confirmed their relationship (Jones et al., 2006; Parasuraman and Grewal, 2000). Therefore, whereas TAM explains how Perceived Usefulness and Perceived Enjoyment are linked to intentions to use and actual use, MEC theory particularly covers the relationships between attributes, benefits, and values and thus additionally provides the basis for the connection between utilitarian and hedonic benefits and values. This benefit-value-intention linkage forms the basis for our research model.

3 Research Model

Based on the theoretical background, this study states that repeat use intention of SST is determined by utilitarian and hedonic value. It adopts a two-dimensional conceptualisation of customer value deriving from underlying benefits and leading to repeat use intention. Both values are operationalised as latent and formative second-order constructs formed by the underlying benefits as sources of their value. The benefit-value-intention linkage based on MEC theory as well as the connection between usefulness, enjoyment, intention to use, and actual use derived from TAM form the basis for the development of our model. The proposed relationships are shown in Figure 1 and discussed below.

Utilitarian and hedonic value are important results which determine a customer's future behaviour choices through feedback loops into the decision processes (Babin et al., 1994). Consequently, customers should have higher repeat use intentions if SST can provide higher utilitarian and hedonic value. Therefore, we propose the following hypotheses:

H1: Utilitarian value influences customers' repeat use intention positively.

H2: Hedonic value influences customers' repeat use intention positively.

Cheung et al. (2003) and van der Heijden et al. (2003) show that online repeat purchase intentions differ, depending on prior experience. We assume that this is similarly applicable to SST. Once customers have learned how to use SST, this positive or negative experience influences their future use intention accordingly. Therefore, we propose the following relationship:

H3: Prior experience with SST influences repeat use intention.

MEC theory states that customers choose actions that avoid undesired and produce desired consequences. Therefore, we presume that they learn from their experiences with SST and appreciate different values depending on their experience level. Kim and Gupta (2009) state that experienced customers are better than potential customers at evaluating attributes due to their experience, and they update the appraisals of the criteria through successive purchases (Kim and Gupta, 2009). Accordingly, a higher experience level may shift customers' focus between hedonic value, for example derived from the excitement of first usage, and utilitarian value. Hence, we also propose the following hypotheses:

H4: Prior experience moderates the influence of utilitarian value on repeat use intention.

H5: Prior experience moderates the influence of hedonic value on repeat use intention.

To monitor possible disruptive effects, we use the four control variables technology affinity, gender, age, and education.

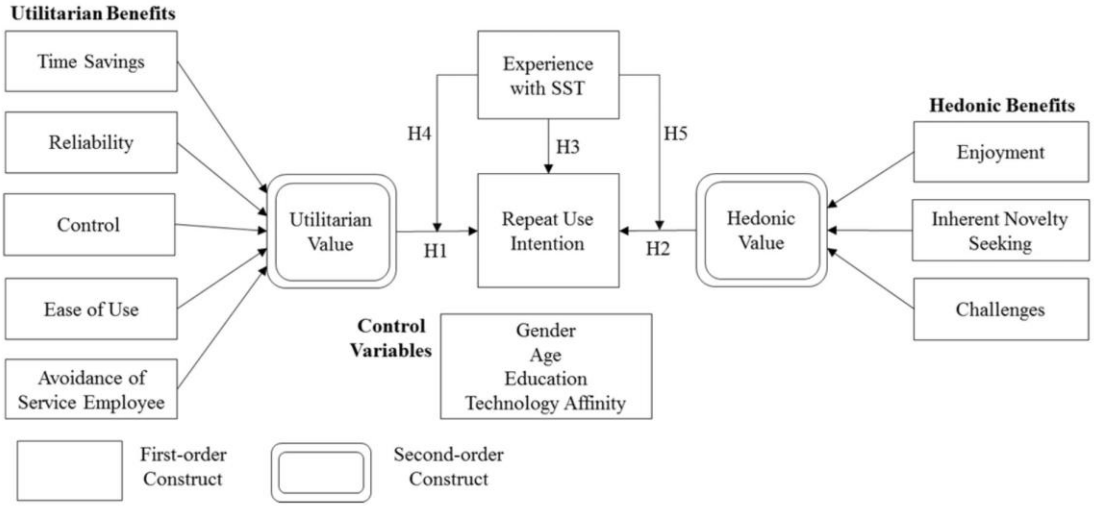

Figure 1. Research model.

4 Research Methodology and Results

For data collection, this study adopts the field survey methodology. We considered a survey of customers of a store providing SST to be an effective method for capturing the proposed constructs and their impacts on repeat use intention (cf. Chiu et al., 2012). In the following, we provide details with respect to the development of the measures, the administration of the survey, and the analysis via Structural Equation Modelling (SEM) techniques.

4.1 Measurement development

We adapted measures from previously validated multi-item scales to foster reliability and validity of measurement. The design of the survey followed standard instrument construction procedures (Atteslander, 2010). Items for measuring utilitarian value were adapted from Dabholkar (1996). To measure hedonic value, we combined constructs from Dabholkar (1996), Mehrabian and Russell (1974), and Novak et al. (2000) and adapted them to the context of SST. Definitions of each construct have been given in Section 2. Items and measurement scales are provided in the appendix. We use a five-point Likert scale, scaled from strongly disagree (1) to strongly agree (5).

4.2 Survey administration

We administered a survey consisting of questions capturing the constructs encompassed in the research model. The target group were customers of a German IKEA store. IKEA was chosen, because

it has already introduced SST in terms of self-service kiosks in Germany some years ago thus enabling us to gain data from customers with different experience levels. That way, we could revert to a big and diverse group of customers. For this study, a total of 455 customers were asked to report about their motivations for using the self-service kiosks. The survey yielded a total of 433 complete and valid responses for data analysis. Table 3 provides demographic information about the respondents.

Measure	Items	
Gender	Male (n=157; 36.26%)	Female (n=276; 63.74%)
Age	14-19 (n=42; 9.70%)	40-49 (n=53; 12.24%)
	20-29 (n=199; 45.96%)	50-59 (n=37; 8.55%)
	30-39 (n=97; 22.40%)	>60 (n=5; 1.15%)
Education	University (Master, Bachelor) (n=154; 35.57%)	Elementary school (n=121; 27.94%)
	Secondary Education (n=156; 36.03%)	No degree (n=2; 0.46%)

Table 3. Demographic information about the respondents (n=433)

4.3 Analysis and results

The research model includes two construct types: first-order constructs (utilitarian and hedonic benefits) and second-order constructs (utilitarian and hedonic value). In the following, we apply a two-step approach (cf. Anderson and Gerbing, 1988; Chiu et al., 2012). The first step examines the composition of the first-order constructs (measurement model), while the second step tests the structural relationships among the latent second-order constructs (structural model). The objective is to ensure the reliability and validity of the measures before examining the structural model parameters (Anderson and Gerbing, 1988; Chin et al., 2003). For our analysis, we chose Partial Least Squares (PLS) and the software package Smart PLS 2.0M3 for the following reasons: First, PLS is recommended for studies including formative constructs as it enables latent constructs to be modelled both as formative and reflective indicators (Lowry and Gaskin, 2014). Second, PLS uses a component-based approach and thus places minimal restrictions on sample size, measurement scales, and residual distribution (Chin, 1998). We operationalise utilitarian and hedonic value as formative second-order constructs as they are latent variables composed of manifest measurement variables causing changes in them.

4.3.1 Measurement model

The second-order constructs were measured by the observed variables for the first-order constructs. We used the approach of repeated manifest variables. This "repeated indicator" approach works very well if the second-order construct is endogenous and formative. The first-order constructs perfectly predict the repeated indicators in the second-order constructs, because they also comprise those indicators (Lowry and Gaskin, 2014). As a result, our research model can be analysed using the standard PLS algorithm. In detail, the second-order construct utilitarian value was measured by the observed manifest variables for time savings (TS), control (CO), reliability (RE), ease of use (EU), and avoidance of service employee (AS), while hedonic value was measured by the variables for enjoyment (EN), inherent novelty seeking (INS), and challenges (CH) (see appendix).

To evaluate the measurement model, we examined reliability and internal consistency of the measures as well as convergent and discriminant validity (via item loadings) (Chin et al., 2003). Reliability was analysed using composite reliability (CR) values which should exceed the commonly acceptable threshold 0.7 (Fornell and Larcker, 1981). Table 4 shows that all CR values satisfy this condition.

Convergent validity was analysed based on two requirements: First, the indicator loadings have to exceed 0.5 (Gefen and Straub, 2005). Hair et al. (2009) suggest that for a sample size that large, even loadings in the 0.3 range suffice. According to Hulland (1999), more important than deleting an item is a model's "consistency at large", suggesting that smaller loadings are equally acceptable if the construct reliability does not change substantially. Second, the average variance extracted (AVE) of each

construct should be higher than the variance due to the measurement error for that construct. Nunally (1979) recommends that the AVE should surpass a 0.5 threshold. As evident in Table 4, the AVE values meet the requirement. Table 5 shows that all of the items exhibit a loading higher than 0.5 on their respective construct. The only exception is AS1 with a loading value of 0.47, but due to the fact that the deletion does not result in a change in reliability, we follow the "consistency at large" approach and keep the item. Thus, the conditions for convergent validity are satisfied.

Construct	Items	CR	Mean	AVE	Construct	Items	CR	Mean	AVE
TS	4	0.86	4.18	0.60	EN	4	0.88	3.64	0.65
RE	4	0.86	4.28	0.62	INS	3	0.82	3.73	0.62
CO	3	0.81	4.00	0.60	CH	2	0.83	2.09	0.71
EU	3	0.86	4.45	0.66	RUI	3	0.96	4.37	0.89
AS	2	0.72	3.66	0.59	TA	3	0.87	4.14	0.69

Table 4. Descriptive statistics of variables.

	TS	RE	CO	EU	AS	EN	INS	CH	RUI	TA
TS1	**0.72**	0.31	0.19	0.40	0.28	0.21	0.09	-0.03	0.36	0.06
TS2	**0.81**	0.40	0.33	0.42	0.25	0.21	0.16	0.00	0.37	0.14
TS3	**0.72**	0.25	0.28	0.29	0.13	0.23	0.13	0.07	0.22	0.06
TS4	**0.85**	0.43	0.35	0.43	0.26	0.26	0.10	0.08	0.41	0.15
RE1	0.39	**0.77**	0.47	0.39	0.25	0.21	0.12	-0.08	0.40	0.17
RE2	0.21	**0.55**	0.24	0.25	0.21	0.12	0.06	-0.01	0.16	0.18
RE3	0.40	**0.88**	0.40	0.49	0.24	0.25	0.22	0.01	0.40	0.26
RE4	0.40	**0.90**	0.47	0.47	0.28	0.26	0.18	0.02	0.43	0.32
CO1	0.37	0.49	**0.88**	0.38	0.21	0.30	0.21	0.02	0.38	0.31
CO2	0.26	0.37	**0.84**	0.28	0.10	0.27	0.30	0.08	0.23	0.25
CO3	0.22	0.21	**0.55**	0.10	0.05	0.25	0.09	0.18	0.14	0.10
EU1	0.46	0.45	0.39	**0.80**	0.19	0.25	0.21	-0.02	0.34	0.21
EU2	0.38	0.43	0.26	**0.88**	0.34	0.16	0.23	-0.07	0.34	0.21
EU3	0.37	0.40	0.21	**0.76**	0.29	0.10	0.17	-0.08	0.27	0.18
AS1	0.06	0.08	-0.05	0.08	**0.47**	-0.03	-0.03	-0.11	0.13	0.02
AS2	0.31	0.32	0.20	0.34	**0.98**	0.26	0.14	-0.05	0.38	0.20
EN1	0.30	0.28	0.34	0.23	0.24	**0.86**	0.36	0.31	0.37	0.18
EN2	0.08	0.02	0.15	0.01	0.04	**0.77**	0.19	0.38	0.16	0.09
EN3	0.43	0.42	0.40	0.36	0.34	**0.73**	0.30	0.09	0.50	0.21
EN4	0.16	0.18	0.24	0.10	0.15	**0.87**	0.32	0.37	0.25	0.10
INS1	0.12	0.18	0.22	0.15	0.04	0.36	**0.87**	0.21	0.20	0.27
INS2	0.02	0.13	0.06	0.25	0.20	0.03	**0.58**	-0.06	0.11	0.17
INS3	0.19	0.15	0.29	0.24	0.13	0.34	**0.87**	0.11	0.28	0.29
CH1	-0.10	-0.16	-0.11	-0.17	-0.12	0.14	0.01	**0.71**	-0.13	-0.15
CH2	0.09	0.04	0.16	-0.02	-0.04	0.40	0.19	**0.96**	0.08	0.04
RUI1	0.44	0.45	0.33	0.39	0.38	0.38	0.26	0.01	**0.95**	0.26
RUI2	0.39	0.40	0.32	0.33	0.31	0.34	0.19	0.01	**0.93**	0.21
RUI3	0.44	0.45	0.34	0.38	0.36	0.39	0.30	0.03	**0.95**	0.28
TA1	0.10	0.23	0.21	0.20	0.15	0.09	0.23	-0.03	0.20	**0.87**
TA2	0.13	0.27	0.32	0.23	0.19	0.26	0.35	0.06	0.27	**0.91**
TA3	0.10	0.25	0.22	0.20	0.14	0.06	0.18	-0.10	0.19	**0.70**

Table 5. PLS confirmatory factor analysis and cross-loadings.

Discriminant validity was assessed by its cross-factor loadings. The loading in absolute terms of each item on its assigned construct should exceed its loadings on all other constructs (Chin, 1998). Table 5 shows that each construct satisfies this condition. In addition, the correlations among the constructs should be lower than 0.85 (Kline, 1998), which is also fulfilled (cf. Table 6). Third, the square root of the AVE of each construct should exceed the correlations of the construct with the other constructs (Fornell and Larcker, 1981). As evident in Table 6, these requirements are well met and the measures demonstrate discriminant validity. Given the strong evidence for convergent and discriminant validity, the scales exhibit good internal consistency and reliability, and the measurement model was deemed acceptable.

	TS	RE	CO	EU	AS	EN	INS	CH	RUI	TA
TS	**0.78**									
RE	0.46	**0.79**								
CO	0.38	0.51	**0.77**							
EU	0.50	0.52	0.36	**0.81**						
AS	0.30	0.31	0.17	0.33	**0.77**					
EN	0.30	0.28	0.35	0.21	0.23	**0.81**				
INS	0.16	0.19	0.27	0.25	0.12	0.37	**0.79**			
CH	0.04	-0.02	0.09	-0.07	-0.07	0.36	0.15	**0.84**		
RUI	0.45	0.46	0.35	0.39	0.37	0.39	0.27	0.02	**0.95**	
TA	0.14	0.30	0.31	0.25	0.19	0.18	0.32	-0.02	0.27	**0.83**
Note: Pearson correlation coefficients with absolute value > 0.1120 are significant at $p < 0.01$; > 0.0792 at $p < 0.05$; >0.0618 at $p < 0.1$. Square root of AVE is in bold.										

Table 6. Correlations among constructs and square root of AVE.

4.3.2 Structural model

To examine the explanatory power of the basic model (referring to hypotheses 1-3), we analysed the structural paths as well as the R^2 score of the endogenous variable. The research model was tested conducting 433 bootstrap runs. The results are shown in Figure 2. They reveal that all of the paths show significance, and the basic model explains 51.4% of the variance of repeat use intention, which underlines that the model explains the cohesions well and has a good fit.

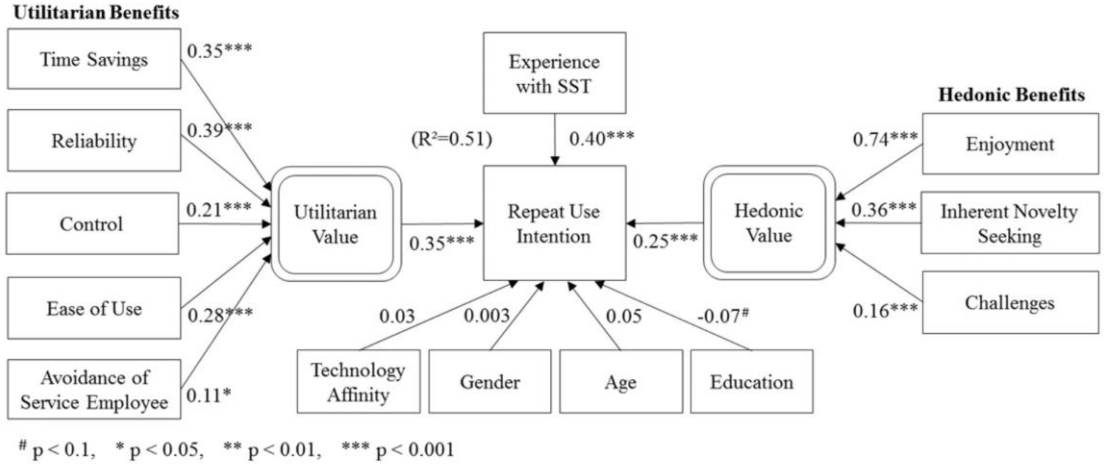

Figure 2. PLS results of the basic research model.

The results of the structural model show that based on the data of all respondents, utilitarian value (β=0.35) and hedonic value (β=0.25) both influence repeat use intention positively. This is in line with

our expectations (cf. hypotheses 1 and 2). The comparison of the path coefficients based on Johnson et al. (1987) reveals that the effect of utilitarian value on repeat use intention is significantly stronger (t=1.98; p<0.05) than the effect of hedonic value. The results also reveal that all proposed constructs of utilitarian value which are time savings (β=0.35, p<0.001), reliability (β=0.39, p<0.001), control (β=0.21, p<0.001), ease of use (β=0.28, p<0.001), and avoidance of service employee (β=0.11, p<0.05) constitute significant components. Weight comparisons based on Johnson et al. (1987) show that among utilitarian benefits, reliability and time savings have higher influence on utilitarian value (p<0.05) than control, ease of use, and avoidance of service employee. This does not seem surprising in today's fast paced world where topics such as security and reliability are becoming increasingly important. Customers may fear that traditional counters are too slow due to inefficiencies of service employees or inescapable interactions. Confirming our expectations, enjoyment (β=0.74, p<0.001), inherent novelty seeking (β=0.36, p<0.001), and challenges (β=0.16, p<0.001) were found to have significant positive influence on hedonic value. By far the most influential construct is enjoyment. The weight comparison (Johnson et al., 1987) showed that the differences are statistically significant (p<0.001). Education was found to have a slightly significant influence (p<0.1), whereas technology affinity, age, and gender were found to have no significant influence on repeat use intention at all. Further, our findings indicate that experience has a significant positive effect on repeat use intention (β=0.40, p<0.001), confirming our expectations (cf. hypothesis 3).

4.3.3 Multi-group analysis

To gain deeper insights into how customer motivations for using SST differ with varying SST experience (cf. hypotheses 4 and 5), we conducted pairwise comparisons of the path coefficients from utilitarian value and hedonic value to repeat use intention in a separate multi-group analysis. Thereby, we distinguished three groups: First, users who had used SST for the first time (N_1=51), second, users with medium experience, meaning they had used it rarely or sometimes (N_2=127), and third, users with a high experience level who had used it often or always (N_3=255). As utilitarian and hedonic value are formative second-order constructs, we used a multiple-group approach to analyse and compare the three groups (Baron and Kenny, 1986). We employed the following formula (cf. Keil et al., 2000):

$$t = (\beta_i - \beta_j) \Big/ \left[\sqrt{\frac{(N_i-1)^2}{N_i+N_j-2} * SE_i^2 + \frac{(N_j-1)^2}{N_i+N_j-2} * SE_j^2} * \sqrt{\frac{1}{N_i} + \frac{1}{N_j}} \right]$$

with t being the t-statistic with N_i+N_j-2 degrees of freedom, N_i the sample size of the data set for group i, SE_i the standard error of the path in the structural model for group i, and β_i the path coefficient in the structural model for group i.

The results show that for users with low experience hedonic value (β=0.58) is more important than utilitarian value (β=0.36). The reason may be that they do not entirely realise the utilitarian benefits, because they are focused on the fun factor. Consequently, for them hedonic reasons prevail. For users with medium experience, the result is reversed: for them, utilitarian value is more important with respect to repeat use intention (β=0.51) than hedonic value (β=0.18). Between the two respective groups we observed significant differences in the influence of hedonic value (t=4.88; p<0.001) as well as in the influence of utilitarian value (t=1.94; p<0.1). Similarly, for users with high experience, utilitarian value (β=0.41) is more important than hedonic value (β=0.27). However, compared to users with medium experience, the influence of utilitarian value decreases (from β=0.51 for medium experienced users to β=0.41) while the influence of hedonic value increases (from β=0.18 for medium experienced users to β=0.27). While the difference between the path coefficients for hedonic value and users with high versus low experience is significant (t=2.75; p<0.01), we did not observe significant differences for their utilitarian values as well as for users with high versus medium experience. Overall, the importance of utilitarian value did not vary that much for the three groups (β between 0.36 and 0.51) compared to the weight of hedonic value (β between 0.18 and 0.58). An explanation for the high difference in the influence of hedonic value may be that, once people know how SST work, the hedonic

aspect decreases. Indeed, the excitement of first usage may decline rapidly, leading to a significant decrease of the influence of hedonic value on repeat use intention. As a consequence, utilitarian value exceeds the weight of hedonic value, leading to a contrary weight allocation for medium experienced customers. Overall, the results meet our expectations, namely that prior experience moderates the influence of utilitarian value and hedonic value on repeat use intention (cf. hypotheses 4 and 5).

5 Discussion

5.1 Implications for theory and practice

Prior research has analysed intention to use of various technologies but the reasons for repeat use intention of SST depending on utilitarian and hedonic values have not been investigated in sufficient detail yet. Against this background, we developed a multidimensional research model to capture an individual's utilitarian and hedonic motivations for the repeat use intention of SST. Our results show that hedonic value is of particular importance for repeat use intention of SST. Whereas analyses about other technologies or technologies in general often solely refer to enjoyment as hedonic component (e.g. Curran and Meuter, 2007; Dabholkar, 1996; Davis et al., 1992), we found that for SST the hedonic factors inherent novelty seeking and challenges must not be ignored. The reason may be that SST encompass a specific do-it-yourself character where customers do not only give orders and wait for the results, but they are responsible for the whole process and thus the results to a certain extent. Supplementary, it is necessary to note that the utilitarian benefit reliability attains special distinction for SST. The reason may be that the customers are in charge of the whole process and thus the reliability of the technology might be more important than in the context of other technologies. In fact, customers may need a certain feeling of reliability when they use SST on their own, in order to really use them. Our study contributes to theory in various ways. First, prior research shows that aside from utilitarian influence factors hedonic influence factors play an important role in explaining the adoption of technology (Agarwal and Karahanna, 2000; Dabholkar, 1996; van der Heijden, 2004; Venkatesh, 2000; Venkatesh et al., 2012). However, little is known to date about the composition of hedonic value of SST. We contribute to this gap by combining both the utilitarian and the hedonic view in a multidimensional research model that captures an individual's motivations for repeat use intention of SST. In so doing, we complement the approach of Dabholkar (1996) and Meuter et al. (2000) by proposing a composition of hedonic value which, like utilitarian value, significantly influences customers' repeat use intention. Thus, we extend the prior understanding of why customers are willing to use SST and even more, why they are willing to use it repeatedly. Second, previous studies have shown that the factors that motivate initial or repeat purchase intention when using technologies are quite different, depending on prior experience. Hence, experience has a moderating role on initial or repeat use intention in various contexts, but still, little is known about how that moderates the importance of utilitarian and hedonic value for the customer. We complement this research (cf. e.g. Cheung et al., 2003; Kim and Gupta, 2009; Parasuraman, 1997; van der Heijden et al., 2003) by expanding it to SST and by conducting an in-depth analysis to enrich current research about utilitarian value, hedonic value, and repeat use intention in the context of SST considerably. We show that prior experience significantly moderates the influence of utilitarian and hedonic value on repeat use intention of SST.

Additionally, this study has several implications for practice. First of all, firms have to recognise that utilitarian and hedonic value both influence repeat use intention positively. Therefore, companies have to design SST in such a way that they address not only task-related benefits such as time savings, reliability, or control (Bitner et al., 2002; Dabholkar, 1996; Dabholkar et al., 2003; Meuter et al., 2000) but also hedonic benefits such as enjoyment, novelty seeking, and challenges that provide "self-fulfilling value to the user" (van der Heijden, 2004, p. 696). Furthermore, as hedonic value is of particular importance for repeat use intention for users who have used SST for the first time, firms need to highlight the fun factor of SST usage for this target group in particular and keep up with new trends in the self-service industry. The use of group buying, social networking, and gaming features may

serve as examples. This is all the more important if firms aim to increase the usage rate of their SST and have to address people who have rarely used SST so far.

5.2 Limitations

Our study provides interesting new insights with respect to customers' repeat use intention of SST. However, a number of limitations still remain which can serve as starting points for future research. First, our study focuses on self-service kiosks, which constitute only one particular type of SST. We decided to do so in a first step to ensure a consistent understanding and to prevent mixing distinct effects that may arise for different types of SST. However, future research should examine a wider range and different types of SST (e.g., SST provided over the internet) in order to substantiate our findings. Second, we collected data for one specific case which may limit the generalizability of our findings. Actually, the main part of IKEA's customers consists of females and young males. Therefore, our sample may not be representative for the totality of SST users. However, our results reveal that age and gender do not have a significant influence on repeat use intention. Moreover, since our survey was carried out in a real customer service setting, we are confident that our rich data set provides a solid foundation for testing the research model.

6 Conclusion

The current study aims to improve our understanding why customers are willing to use SST. Based on MEC theory we examined the multidimensional nature of utilitarian and especially hedonic value and their relative importance in determining repeat use intention of SST. We complement existing research providing a composition of hedonic value which, like utilitarian value, significantly influences customers' repeat use intention. Our findings show that the constructs enjoyment, inherent novelty seeking, and challenges constitute significant components of hedonic value. Both utilitarian and hedonic value influence customers' repeat use intention positively, with the influence of utilitarian value prevailing. More detailed multi-group analyses with respect to customers' prior experience with SST reveal that this result does not hold for all customers. Indeed, for users with low experience hedonic value is more important than utilitarian value. Overall, our study is the first to compare the relative importance of utilitarian and hedonic value in dependence of customers' prior experience of using SST, and we confirmed the key roles of these constructs in influencing repeat use intention. We hope that our work opens doors for further research activities in this exciting field.

Appendix A – Questionnaire Items

Notes: Anchors for these scales are: 1=Strongly disagree; 2=Slightly disagree; 3=Neither agree nor disagree (neutral); 4=Slightly agree; 5=Strongly agree

Time Savings (TS) (adapted from Dabholkar, 1996)	
TS1	I needed a lot of time for using the SST.
TS2	The paying process with the SST was very quick.
TS3	The waiting time for using the SST was very quick.
TS4	Shopping with the SST allows me to save time.
Ease of Use (EU) (adapted from Dabholkar, 1996)	
EU1	The usage of the SST is complicated.
EU2	The usage of the SST takes a lot of effort.
EU3	The usage of the SST is slow and complex.
Reliability (RE) (adapted from Dabholkar, 1996)	
RE1	Using the SST is accurate (means I will get just what I ordered).
RE2	Using the SST results in errors in the order.
RE3	Using the SST is something I don't expect to work very well.

RE4	Using the SST is reliable.
Control (CO) (adapted from Dabholkar, 1996)	
CO1	The usage of the SST gives me control.
CO2	The usage of the SST lets me be in charge of the right result.
CO3	The usage of the SST lets me be in charge of the right price.
Avoidance of Service Employee (AS) (adapted from Dabholkar, 1996)	
AS1	Personal attention by the service employee is not important to me.
AS2	It does not bother me to use a machine when I could talk to a person instead.
Enjoyment (EN) (adapted from Dabholkar, 1996)	
EN1	It is enjoyable to use the SST.
EN2	It is exciting to use the SST.
EN3	It is pleasant to use the SST.
EN4	It is interesting to use the SST.
Inherent Novelty Seeking (INS) (adapted from Mehrabian and Russell, 1974)	
INS1	I am always seeking new ideas and experiences.
INS2	When things get bored I like to find new and unfamiliar experiences.
INS3	I prefer a routine way of doing things to experimenting with new things.
INS4	I like to experience novelty and change in my daily routine.
Challenges (CH) (adapted from Novak et al., 1998)	
CH1	Using the SST challenged me to perform to the best of my ability.
CH2	Using the SST provided a good test of my skills.
Repeat Use Intention (RUI) (adapted from Hu et al., 2011 and Venkatesh et al., 2003)	
RUI 1	In the future, I am very likely to use SST.
RUI 2	I expect I will use SST in the next months.
RUI 3	I intend to use SST in the future.
Technology Affinity (TA) (adapted from Venkatesh et al., 2003)	
TA1	I use a lot of new technologies in my everyday life.
TA2	I feel good about using new technologies.
TA3	It is pleasant for me to deal with new technologies.

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2.2 Paper 2: Customers' Intention to Switch to Mobile Self-Service Technologies

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[3] Please note that in Paper 2, motivations are called determinants as the valence framework, which lays the foundation for the study comprised in Paper 2, operates with determinants. Yet, within the scope of this dissertation, the meaning of motivations and determinants is similar.

CUSTOMERS' INTENTION TO SWITCH TO MOBILE SELF-SERVICE TECHNOLOGIES

Research paper

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Abstract

Self-service technologies (SST) such as online check-ins are more and more becoming an integral part of our daily routines. However, while kiosk SST such as automated teller machines in banking are widely used, mobile SST are just beginning to capture the market. Enforcing customers to switch from kiosk to mobile SST sometimes still turns out to be difficult due to routine seeking, privacy risks, or fear of complex user interfaces. As a result, users are locked into a status quo and do not switch to mobile technologies. Thus, there is a need to better understand why customers switch from kiosk to mobile SST. Against this background, the aim of this paper is to gain a better understanding of the factors influencing customers' intention to switch from kiosk to mobile SST. We investigate the positive and negative determinants, which constitute the positive and negative valence of mobile SST as factors influencing the intention to switch. Our study expands existing research by outlining the particular importance of the positive valence for the customers' intention to switch. We further show that multifunctionality, compatibility with the lifestyle, and enjoyment constitute the most crucial positive determinants rather than prestige reasons.

Keywords: Self-service technologies, Mobile technology, Valence framework, Intention to switch.

1 Introduction

Due to the rapid development in information technology, self-service technologies (SST) have become more and more prevalent amongst service providers (Scherer et al., 2015). Automated teller machines in banking, self-checkout systems in supermarkets, and services over the internet such as online check-in for flights are taken for granted in today's fast-paced world (Wang et al., 2013). SST are technological interfaces "that enable customers to produce a service independent of direct service employee involvement" (Meuter et al., 2000, p. 50). In particular, mobile SST are gaining increasing importance. The number of mobile users is expected to grow from 4.8 billion in 2015 to 5.5 billion in 2020. This implies that 70 percent of the global population will be using mobile devices (Cisco, 2016). Compared to kiosk SST (e.g., ATM, self-checkout systems in supermarkets) where customers act anonymously, mobile SST offer companies the opportunity to collect valuable data on their customers. For this reason, companies endorse their customers to switch from "anonymous" SST, such as kiosks, to mobile SST. Yet, the switch from kiosk to mobile SST sometimes still turns out to be difficult due to potential privacy risks, performance risks, fear of complex user interfaces, or the customers' preference to stick with routines. Therefore, it is of central importance to understand the driving forces of customers' intention to switch to mobile SST and to adapt the services to fulfil customers' motives for using them.

Prior research has begun to investigate the adoption of SST (e.g., Curran and Meuter, 2005; Dabholkar and Bagozzi, 2002; Meuter et al., 2005). They found, for example, that the adoption is driven by perceived usefulness, perceived ease of use, time savings, reliability, control over the process, or perceived enjoyment (e.g., Agarwal and Karahanna, 2000; Venkatesh et al., 2012) as well as image, compatibility, and alternative attractiveness (Bansal et al., 2005; Chang et al., 2014; Lu et al., 2011). Further research concerning the reasons for SST rejection explained that user resistance behaviour prevents users from switching between technologies (Laumer et al., 2016b). That implies that users are locked into a status quo and therefore do not switch to alternatives (Polites and Karahanna, 2012). Reasons for rejection can be amongst others switching costs or a response to threats that an individual associates with a new system (Kim and Kankanhalli, 2009; Marakas and Hornik, 1996). Although factors leading to adoption and rejection of SST have been explored, existing research still lacks an in-depth understanding of the factors influencing the intention to switch from kiosk SST to mobile SST. Therefore, the aim of this paper is to gain a better understanding of the factors influencing the intention to switch from kiosk SST to mobile SST. More specifically, we investigate the positive and negative determinants influencing the intention to switch. As these factors vary between mobile SST and other SST, we examine the multidimensional nature of the positive and negative determinants and investigate their relative importance in determining the intention to switch. The research questions driving this study are: 1) *What is the relative importance of the positive and the negative valence for the intention to switch from kiosk to mobile SST?* 2) *What are the determinants of the positive and the negative valence of mobile SST?* To investigate these questions we build upon the valence framework, which assumes that customers perceive products and services as having both positive and negative attributes and combines *positive* and *negative valence determinants* as the fundamental aspects for customer decisions (Peter and Tarpey, 1975).

The remainder of the paper is organised as follows: Section 2 provides an overview of the related literature. In Section 3, we describe the research model. Afterwards, we explain the research methodology and present the results of our analysis in Section 4. In Section 5, we discuss our results and present theoretical and practical implications. Finally, we conclude our paper with a brief summary of our findings in Section 6.

2 Theoretical Background

SST offer customers a technological interface that enables access to services independent of physical interaction with a service employee (Curran and Meuter, 2005). Compared to personal service encounters, SST have changed the nature of the service delivery process in depth (Wang et al., 2013; Meuter et al., 2000). SST can be differentiated based on the technology used, namely interactive kiosk, internet (incl. mobile), and interactive voice response (Meuter et al., 2000) whereas the internet-based SST type is the most common (Evanschitzky et al., 2004; Yen and Gwinner, 2003).

2.1 Adoption theory and outcomes of SST adoption

For determining the success of information system projects, user acceptance is widely considered as the most important factor (Davis, 1993). It is conceptualized as an outcome variable in a psychological process when users make decisions about technology (Dillon and Morris, 1996) and can be defined as "the demonstrable willingness within a user group to employ information technology (IT) for the tasks it is designed to support" (Dillon and Morris, 1996, p. 3). The most prevalent model for predicting IT acceptance is Davis' (1989) Technology Acceptance Model (TAM) deriving from the Theory of Reasoned Action (TRA), which conveys that beliefs influence intentions, and intentions in turn influence one's actions (Ajzen and Fishbein, 1975). The TAM links "external variables to [...] actual use" (Davis and Venkatesh, 1996, p. 20) and therefore builds a complete causal chain. Technology adoption research has analysed several factors leading to adoption. They found that the adoption is driven by, among others, perceived usefulness, perceived ease of use, or time savings, reliability, control over the process, or perceived enjoyment (e.g., Agarwal and Karahanna, 2000; van der Heijden, 2004; Venkatesh et al.,

2012) as well as image, compatibility, and alternative attractiveness in the concrete context of mobile service (Bansal et al., 2005; Chang et al., 2014; Lu et al., 2011). Individuals' resistance to technologies and their respective use has drawn much less attention so far (Cenfetelli, 2004; Lapointe and Rivard, 2005; Laumer et al., 2016a; Kim and Kankanhalli, 2009). From early on, resistance has been identified as a key factor for implementation success (Laumer and Eckhardt, 2012). It was simply considered as the opposite part of acceptance (Venkatesh and Davis, 2000; Venkatesh and Morris, 2000). But it is more than only the flip side of the coin. Causes for resistance against information system implementation can be amongst others switching costs and perceived threats (Bhattacherjee and Hikmet, 2007; Kim and Kankanhalli, 2009; Laumer et al., 2016b). Before switching to an alternative, individuals evaluate relative costs (i.e. causes for resistance) and benefits of the change (i.e. causes for acceptance) (Kim and Kankanhalli, 2009). In this paper, we state that both sides – i.e. positive and negative determinants – need to be considered when investigating individuals' switching intentions. Therefore, we use intention to switch as outcome variable which is influenced by positive and negative determinants which users perceive from actual technology switching.

2.2 Determinants of intention to switch to mobile SST

Switching behaviour is determined by the perceived advantages and disadvantages of a technology. Therefore, to investigate the determinants influencing intention to switch to a technology, the two sides of a technology which are its positive and negative determinants need to be combined. Intention to switch has been examined in various fields, for instance in the banking and insurance industry, in retail stores as well as in the context of credit cards, car insurance, car repair, hairstyling, fixed-telephone and banking services (e.g., Chang et al., 2014; Ye and Potter, 2011; Lopez et al., 2006). Human geography differentiates between voluntary and involuntary migrants. While voluntary migrants can freely decide to migrate (Jackson, 1986), involuntary migrants have to migrate due to certain factors (e.g., war) (Bansal et al., 2005). Users of technologies can be both. There are on the one hand voluntary migrants which can freely choose to migrate (switch) between technologies and on the other hand involuntary migrants which have no choice but to migrate (switch) because their current technology service is not continued (Chang et al., 2014). This study examines SST and hence encompasses both types of migrants. As opposed to products or services where users depend on one single vendor (e.g., car insurance), consumption of other products or services (e.g., bank accounts or SST) is not limited to one vendor (Ye et al., 2008; Ye and Potter, 2011). Therefore, switching in the case of SST is rather focus shifting than a total substitution. Even in the event of total substitution, the process may be stepwise, which results in a simultaneous use of several products for some periods (Chang et al., 2014). Against this background, for this work the definition of switching as "users' partial reduction or full termination in usage of a specific technology product while substituting it with usage of an alternative product that satisfies identical needs" (Ye and Potter, 2011, p. 587) is used.

In order to explain switching behaviour, human geographic literature delivers the "push-pull" framework (Lee, 1966; Moon, 1995). It describes switching as migrating from one location to another. While push factors are negative factors driving individuals to leave their origin and go to a destination, pull factors are considered as advantages dragging the individual towards the destination. Against this background, information systems research used this theoretical lens to explain why and how individuals develop switching intentions between technologies (Bansal et al., 2005; Bhattacherjee and Park, 2014; Chang et al., 2014; Wirth and Maier, 2017). However, this "push-pull" framework also includes mooring factors which are considered as factors that still facilitate or hinder the switching intention. For the purpose of our study, these are not necessary to be investigated, which is why it cannot perfectly depict the basis of our study. However, there is another approach which can more appropriately lay the foundation for this work. It is called the valence framework, which assumes that customers perceive products and services as having both positive and negative attributes (Peter and Tarpey, 1975). The valence framework derives primarily from the psychology and economics literature and investigates customer behaviour by involving "perceived risk" and "perceived benefit" as the two fundamental aspects of customers' decisions. While the perceived risk aspect states that customers aim at minimizing negative

effects, the perceived benefit aspect characterizes customers as aiming to maximize positive effects. Finally, the "perceived value" or valence framework assumes that consumers perceive products as having both positive and negative attributes, and accordingly make decisions to maximize their net valence. The valence framework can be considered a suitable model as it takes into account both positive and negative determinants of a decision (Peter and Tarpey, 1975). Against this background, Lu et al. (2011) identify positive and negative valence determinants for mobile payment usage and analyse how they affect a customer's intention to use. Further studies in the e-commerce environment approve the valence framework as valid model for analysing the positive and negative aspects influencing customer behaviour (Kim et al., 2008; Kim et al., 2009). However, while previous studies show that the valence framework is an adequate model to investigate intention to switch, extensions are required to adapt it to the mobile SST environment and to capture its individual characteristics. Yet, it offers a solid basis to investigate in a first step the positive and negative determinants influencing customers' behaviour decisions, such as the intention to switch. Consistent with the TRA, intention to switch is posited to be an immediate determinant of the actual usage behaviour. Therefore, this study is based on the valence framework as theoretical foundation that encompasses the positive and negative determinants that influence customers' intention to switch to mobile SST.

2.3 Positive and negative valence determinants of mobile SST

The valence framework describes perceived risk as *negative valence*, whereas perceived benefit represents the *positive valence* (Peter and Tarpey, 1975). Due to the innovative nature of mobile SST, however, the *positive* and *negative valence* need to be regarded more in detail – i.e. how they are composed in this concrete context – and adapted accordingly. Our reflections are described in the following.

2.3.1 Positive valence determinants fostering intention to switch

The reasons why customers adopt SST depend upon the benefits, more precisely the *positive valence determinants* they can receive from it (Yan et al., 2013). Reflecting the literature, the most important positive valence determinants of mobile SST are *independence of location and time*, *time savings*, *personalisation*, *compatibility*, *image*, *multifunctionality*, and *enjoyment* (cf. Table 1).

Determinant	References
Independence of location and time	Kim et al. (2009), Lee and Benbasat (2003), Mallat et al. (2008)
Time savings	Alreck and Settle (2002), Dabholkar (1996), Dabholkar et al. (2003), Lee et al. (2013), Meuter et al. (2000)
Personalisation	Adomavicius and Tuzhilin (2005), Chellappa and Sin (2005), Junglas and Watson (2006), Park (2014), Xu et al. (2011)
Compatibility	Lu et al. (2011), Moore and Benbasat (1991)
Image	Lu et al. (2011), Negahban and Chung (2014), Rogers (2010), Venkatesh and Davis (2000)
Multifunctionality	Negahban and Chung (2014)
Enjoyment	Dabholkar (1996), Davis et al. (1992), van der Heijden (2004), Negahban and Chung (2014)

Table 1. Positive valence determinants influencing intention to switch.

First, mobile SST can be accessed 24/7 around the globe. Thus, for example for buying a ticket or using a service, personal presence is not required anymore. Several studies have shown that this *independence of location and time* has a positive impact on the users' attitudes to adopt and use a system. This includes advantages like avoiding queuing and the fact of being independent of opening hours (Kim et al., 2009; Lee and Benbasat, 2003; Mallat et al., 2008). Besides the *independence of place and time*, *time savings* play an important role for using SST (Alreck and Settle, 2002; Dabholkar et al., 2003; Lee and Benbasat, 2003; Lee et al., 2013; Meuter et al., 2000). Customers place special value on reducing or avoiding

waiting time and increasing the speed of service delivery (Dabholkar, 1996) and therefore, if a new technology meets these requirements, they are more likely to switch. A further benefit of mobile SST is the possibility of personalised services (Adomavicius and Tuzhilin, 2005; Chellappa and Sin, 2005; Junglas and Watson, 2006; Xu et al., 2011). *Personalisation* is the ability to provide services and contents tailored to individual users, based on knowledge on their behaviour and preferences (Adomavicius and Tuzhilin, 2005). Although usually private information like social media data or customer profiles have to be collected, *personalisation* can increase the adoption of a new technology and thus the intention to switch (Park, 2014). Another advantage is *compatibility*, which describes the degree of fit between an innovation and a potential adopter's existing values, needs and past experiences as well as his or her lifestyle (Moore and Benbasat, 1991). In the context of mobile SST, peoples' lifestyles will strongly affect their decision to adopt a technology. With mobile SST being an extension of internet SST, people who frequently use internet SST may be less resistant to accept the mobile version. Therefore, users perceiving mobile SST as compatible with their lifestyle can have a greater intention to switch (Lu et al., 2011). Gaining social status can be another important motivation to adopt an innovation (Rogers, 2010; Moore and Benbasat, 1991). *Image* is defined as "the degree to which use of an innovation is perceived to enhance one's image or status in one's social system" (Moore and Benbasat, 1991, p. 195). Individuals are likely to respond to influences within their social systems to establish or maintain a favourable image (Lu et al., 2011; Negahban and Chung, 2014). If important members of a person's social group believe that he or she should switch to mobile SST, the likelihood of actual service switching rises (Venkatesh and Davis, 2000). Besides, mobile SST provide a vast collection of functionalities and a variety of services (Negahban and Chung, 2014). A mobile SST can, for instance, comprise navigation options, information on delays or alternative routes, alternative transportation information, ticket purchasing or special online offers, to name just a few functionalities. Accordingly, this *multifunctionality* can influence the intention to switch to mobile SST and needs to be considered. Finally, *enjoyment* is a further benefit which is described as the extent to which an activity of using a technology is perceived as enjoyable (Davis et al., 1992; Dabholkar, 1996). In information systems research, *enjoyment* is identified to be a key factor, underlying the acceptance of computers or computer systems (Davis et al., 1992; van der Heijden, 2004; Negahban and Chung, 2014). Customers who enjoy products are more likely to actually use or buy them. Dabholkar (1996) states that customers are more likely to use SST if it looks like being fun which leads to the assumption that *enjoyment* increases a customer's intention to switch to mobile SST.

2.3.2 Negative valence determinants hindering intention to switch

Other determinants prevent customers from switching. In the context of mobile SST, amongst the most important are *privacy risk*, *performance risk*, *complexity*, and *routine seeking* (cf. Table 2).

Determinant	References
Privacy risk	Featherman and Pavlou (2003), Lee (2009), Lu et al. (2011)
Performance risk	Featherman and Pavlou (2003), Lee (2009), Wu and Chen (2005)
Complexity	Ebbers et al. (2008), Jäveläinen (2007), Treviño et al. (2000)
Routine seeking	Kunze et al. (2013), Oreg (2003)

Table 2. Negative valence determinants influencing intention to switch.

Privacy risk is defined as the potential loss of control over personal information. This applies when information about a person is used without permission or knowledge (Featherman and Pavlou, 2003). The determinant has been identified as being an important performance-based inhibitor to electronic service evaluation and adoption (Featherman and Pavlou, 2003; Lee, 2009; Lu et al., 2011). It is a major challenge especially for services using sensitive financial information like banking or payment apps (Lee, 2009). We assume that this holds true for all mobile SST using personal data which leads to the assumption that *privacy risk* can decrease the intention to switch. Another negative determinant is *performance risk*, which is explained as the possibility that a service may not perform as it was promised

or advertised. Thus, unexpected losses may be caused, for instance, by a temporal disconnection from the internet or a general breakdown in the server connection (Featherman and Pavlou, 2003; Lee, 2009; Wu and Chen, 2005). Thus, malfunctions may reduce a customer's intention to switch. A further disadvantage influencing the intention to switch is *complexity*, which refers to the amount of interrelated actions necessary in order to solve a problem. The higher the complexity becomes, the more information an individual needs in order to conduct the process correctly (Ebbers et al., 2008). Comparing low involvement products (like basic banking or general insurance) with high involvement products (like mortgage or investment advices), low involvement products do not necessarily require face-to-face channels. But high complex tasks are preferred to be conducted offline, therefore preventing customers from switching to mobile SST (Ebbers et al., 2008; Järveläinen, 2007; Treviño et al., 2000). Regardless of this, using a new technology like mobile SST properly can be a challenge for the customer and he or she may experience it as difficult to go through the process without failure. A feeling of dissatisfaction arises if the customer does not succeed which results in a decrease of the customer's intention to switch (Koufaris, 2002). In addition to that, *routine seeking* has been identified as in important determinant influencing the resistance to change (Kunze et al., 2013; Oreg, 2003). Users may not adopt a new service because switching may require more work in the short term or they simply are not positive about new innovations or changes in their lives (Kunze et al., 2013; Oreg, 2003). Therefore, instead of adopting a new service, users may prefer sticking with their routine with the result that they do not develop an intention to switch to mobile SST.

3 Research Model

Based on the theoretical background, this study states that intention to switch to mobile SST is determined by the *positive* and the *negative valence*. It adopts a two-dimensional conceptualization with the valences consisting of determinants influencing the intention to switch. Both valences are operationalized as latent and formative second-order constructs formed by the underlying determinants. The proposed relationships are shown in Figure 1 and explained below.

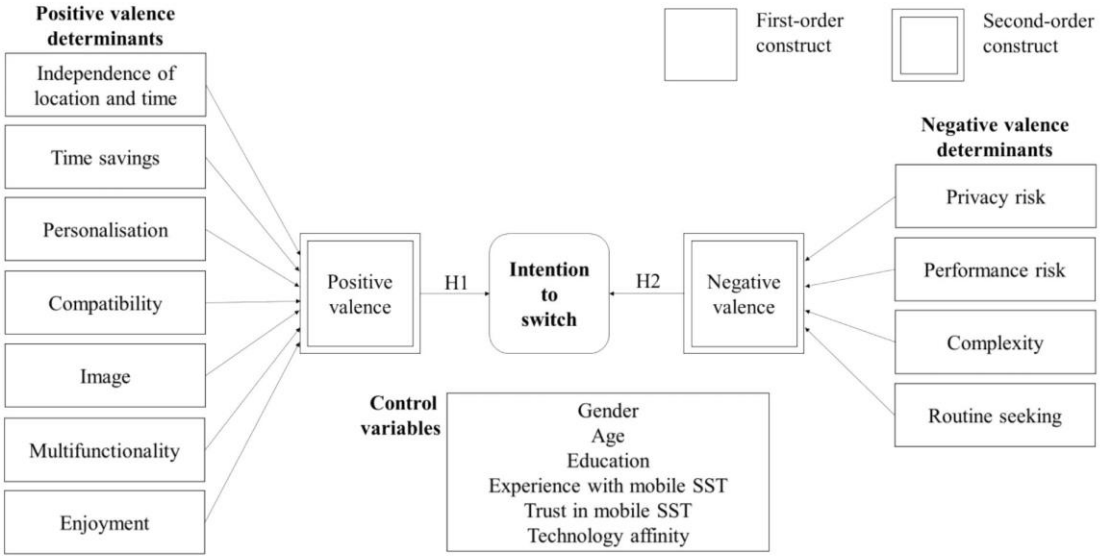

Figure 1. Research model.

The *positive* and the *negative valence* are important factors that influence future behaviour choices of the customers through feedback loops into the decision processes (Babin et al., 1994). In this regard, customers aim to maximize positive and minimize negative effects. Therefore, the *positive valence*

should influence customers' intention to switch positively while the *negative valence* should lead to a lower intention to switch respectively. For this reason, we propose the following hypotheses:

H1: Positive valence influences intention to switch positively.

H2: Negative valence influences intention to switch negatively.

4 Research Methodology and Results

This study adopts a field survey methodology for data collection. As public transportation in Germany offers different well-accepted SST options, we considered a survey at railway stations to be an effective method for capturing the proposed determinants and their impact on the intention to switch. We focussed on two kinds of SST in this study, namely on the switch from kiosk SST to mobile SST as they allow us to analyse the drivers of intention to switch between different kinds of SST with different degrees of anonymity. In the following, we describe the development of the measures, the administration of the survey, and the analysis via Structural Equation Modelling (SEM) techniques.

4.1 Measurement development

We adapted measures from previously validated multi-item scales to foster reliability and validity of the measurement. The design of the survey followed standard instrument construction procedures (Attes-lander, 2010; Moore and Benbasat, 1991). To measure the *positive valence*, we combined constructs from Mallat et al. (2008), Dabholkar (1996), Xu et al. (2011), Moore and Benbasat (1991), Venkatesh and Davis (2000), and Negahban and Chung (2014). Items for measuring the *negative valence* were adapted from Lee (2009), Lu et al. (2011), Järveläinen (2007), Oreg (2003), and Treviño et al. (2000). All constructs were adapted to the context of mobile SST. The items and measurement scales are provided in the appendix. All items were rated to five-point Likert scales ranging from strongly disagree (1) to strongly agree (5). Experience with mobile SST was measured on a five-point scale ranging from never to always (never, rarely, sometimes, often, always).

4.2 Data collection

We administered a survey consisting of questions capturing the constructs encompassed in the research model. We provided a clear description of kiosk SST, mobile SST and the rationale of the questionnaire to assure the interviewees' understanding of the objective. To receive meaningful results, we conducted the survey at two train stations in Germany. Interviewers chose their prospects randomly and not in the sphere of influence of any particular SST. Train stations were chosen as they offer different SST options, amongst them kiosks SST, which are broadly accepted and adopted by the customers, and mobile SST. The survey was conducted on different working days in order to cover a broad range of users with varying demographic variables. Of the 443 surveys collected, 315 usable responses (71.11%) remained for data analysis after removing those from the data set which were not completed entirely or displayed deficient answers. Table 3 lists demographic information of the respondents.

Measure	Items	
Gender	Male (n=146; 46.35%)	Female (n=169; 53.65%)
Age	14-19 (n=45; 14.29%) 20-29 (n=129; 40.95%) 30-39 (n=50; 15.87%)	40-49 (n=35; 11.11%) 50-59 (n=39; 12.38%) >59 (n=17; 5.40%)
Education	University (Master, Bachelor) (n=161; 51.11%) Secondary Education (n=62; 19.68%)	Elementary school (n=90; 28.57%) No degree (n=2; 0.63%)

Table 3. Demographic information about the respondents (n=315).

4.3 Analysis and results

Two construct types compose the research model: first-order constructs (*positive* and *negative valence determinants*) and second-order constructs (*positive* and *negative valence*). We utilise a two-step approach to analyse the hypotheses (cf. Anderson and Gerbing, 1988; Chiu et al., 2014). While the first step tests the composition of the first-order constructs (measurement model), the second step examines the structural relationships among the latent second-order constructs (structural model). This proceeding enables to ensure reliability and validity of the measures before examination of the structural model parameters (Anderson and Gerbing, 1988). We chose Partial Least Squares (PLS) and the software package Smart PLS 3 for our analysis. PLS enables latent constructs to be modelled as formative and reflective indicators and therefore is suggested for studies including formative constructs (Lowry and Gaskin, 2014). Moreover, a component-based approach to estimation is applied, placing minimal restrictions on sample size, measurement scales and residual distribution (Chin, 1998). As *positive* and *negative valence* are latent variables composed of manifest measurement variables causing changes in them, we operationalise them as formative second-order constructs.

4.3.1 Measurement model

The second-order constructs were measured by the observed variables for the first-order constructs. We therefore used the approach of repeated manifest variables. The first-order constructs perfectly predict the repeated indicators in the second-order constructs, as they also comprise those indicators. For endogenous and formative second-order constructs, this "repeated indicator" approach has been proven to work very well (Lowry and Gaskin, 2014). Consequently, the standard PLS algorithm can be used for analysing our research model. The second-order construct *positive valence* was measured by the observed manifest variables for *independence of location and time* (IN), *time savings* (TS), *personalisation* (PE), *compatibility* (CO), *image* (IM), *multifunctionality* (MU) and *enjoyment* (EN). *Negative valence* was measured by *privacy risk* (PR), *performance risk* (PF), *complexity* (CX) and *routine seeking* (RS) (see appendix).

We established reliability and internal consistency of the measures as well as convergent and discriminant validity (via item loadings) to test the adequacy of the measurement model (Chin et al., 2003). Composite reliability (CR) values were used to analyse reliability. As can be seen in Table 4, all CR exceed the commonly acceptable threshold 0.7 (Fornell and Larcker, 1981). Convergent validity was analysed based on two requirements: First, in order to be significant, the indicator loadings need to exceed 0.5 (Gefen and Straub, 2005) which is fulfilled by our model. Due to page limitations, we could not provide a separate table including all indicator loadings. Second, the average variance extracted (AVE) of each construct should be higher than the variance due to the measurement error for that construct and should surpass a 0.5 threshold (Nunnally, 1967). Table 4 shows that all AVE values meet the requirement. All of the items exhibit a loading higher than 0.5 on their respective construct.

Construct	Items	CR	Mean	AVE	Construct	Items	CR	Mean	AVE
IN	3	0.80	4.34	0.57	PR	3	0.92	3.30	0.78
TS	4	0.77	3.53	0.51	PF	3	0.88	3.73	0.68
PE	3	0.87	3.14	0.68	CX	3	0.90	2.30	0.75
CO	3	0.89	3.35	0.73	RS	4	0.88	2.57	0.64
IM	3	0.86	1.88	0.69	IS	3	0.93	3.55	0.82
MU	4	0.88	3.29	0.65	TR	3	0.87	3.99	0.69
EN	4	0.84	3.23	0.58	TA	3	0.89	3.73	0.58

Table 4. Descriptive statistics of variables.

	IN	TS	PE	CO	IM	MU	EN	PR	PF	CX	RS	IS	TR	TA
IN	**0.76**													
TS	0.34	**0.68**												
PE	0.21	0.42	**0.83**											
CO	0.32	0.49	0.40	**0.86**										
IM	-0.05	-0.05	0.09	0.14	**0.83**									
MU	0.31	0.41	0.39	0.52	0.04	**0.80**								
EN	0.23	0.25	0.30	0.47	0.26	0.44	**0.76**							
PR	-0.17	-0.26	-0.12	-0.32	0.02	-0.24	-0.15	**0.88**						
PF	-0.04	-0.02	-0.09	-0.18	-0.12	-0.18	-0.15	0.25	**0.84**					
CX	-0.26	-0.40	-0.11	-0.36	0.08	-0.40	-0.22	0.24	0.13	**0.87**				
RS	-0.24	-0.36	-0.21	-0.24	0.13	-0.27	-0.05	0.20	-0.06	0.30	**0.80**			
IS	0.37	0.47	0.25	0.63	0.09	0.51	0.51	-0.37	-0.16	-0.37	-0.30	**0.90**		
TR	0.23	0.31	0.27	0.32	-0.14	0.38	0.21	-0.29	-0.12	-0.36	-0.32	0.34	**0.83**	
TA	0.27	0.32	0.16	0.50	0.05	0.41	0.46	-0.28	-0.06	-0.47	-0.31	0.58	0.33	**0.85**
Note: Pearson correlation coefficients with absolute value > 0.1120 are significant at $p < 0.01$; > 0.0792 significant at $p < 0.05$; >0.0618 significant at $p < 0.1$. Square root of AVE is in bold.														

Table 5. Correlations among constructs and square root of AVE.

Discriminant validity was assessed first by its cross-factor loadings. The loading in absolute terms of each item on its assigned construct should exceed its loadings on all other constructs (Chin, 1998) which our model well satisfies but again this result could not be displayed due to page limitations. Second, the correlations among the constructs must be lower than 0.85 (Kline and Santor, 1999) which is also fulfilled (Table 5). Third, the square root of the AVE of each construct must exceed the correlations of the construct with the other constructs (Fornell and Larcker, 1981). As can be seen in Table 5, these requirements are well met and therefore, the measures demonstrate discriminant validity. Given the strong evidence for convergent and discriminant validity, the scales exhibit good internal consistency and reliability and the measurement model was deemed acceptable.

4.3.2 Structural model

In order to examine the explanatory power of the structural model (referring to our hypotheses 1 and 2), we determined the structural paths and the R^2 score of the endogenous variable. The result of the path analysis with a bootstrap sample number of 5.000 shows that our hypotheses are supported. All paths show significance and the model explains 58.1% of the variance of intention to switch. This implies that the model explains the cohesions well and the model has a good fit (Hair et al., 2011). The results are presented and discussed subsequently.

The evaluation of our model reveals the following results. First, path analysis shows that based on the data of all respondents, *positive valence* influences intention to switch positively (β=0.40, p<0.001) while *negative valence* exhibits negative influence respectively (β=-0.11, p<0.05). This is in line with our expectations (cf. hypotheses 1 and 2). The comparison of the path coefficients based on Johnson et al. (1987) reveals that the effect of *positive valence* on intention to use is significantly stronger (t=6.21; p<0.001) than the effect of *negative valence*. Second, the results further reveal that all proposed determinants of positive valence, namely *independence of location and time* (β=0.14, p<0.001), *time savings* (β=0.20, p<0.001), *personalisation* (β=0.18, p<0.001), *compatibility* (β=0.31, p<0.001), *image* (β=0.04, p<0.1), *multifunctionality* (β=0.32, p<0.001), and *enjoyment* (β=0.25, p<0.001) constitute significant components. Weight comparisons (Johnson et al., 1987) show that among *positive valence*, *multifunctionality* and *compatibility* exhibit higher influence on *positive valence* (p<0.1) than the other determinants. These findings indicate that determinants related to the "mobile lifestyle" are valued most. Third, *privacy risk* (β=0.46, p<0.001), *performance risk* (β=0.16, p<0.01), *complexity* (β=0.44, p<0.001), and *routine seeking* (β=0.47, p<0.001) were found to have significant positive influence on *negative valence*. *Routine seeking*, *privacy risk*, and *complexity* have a much higher influence than *performance risk*.

Weight comparisons (Johnson et al., 1987) showed that the differences are statistically significant (p<0.001) elucidating that people trust mobile SST and do not expect this technology to have serious functionality errors. This is not without reason in a world where people grow up with mobile SST becoming an integral part of everyone's life. The more a person is exposed to a technology the more the technology as well as its proper functionality are taken for granted. Finally, *experience* (β=0.23, p<0.001) and *technology affinity* (β=0.22, p<0.001) exhibit significant influences while *education* shows a slightly significant influence (β=-0.08, p<0.05) and *gender*, *age* and *trust* were found to have no significant influence on intention to switch at all.

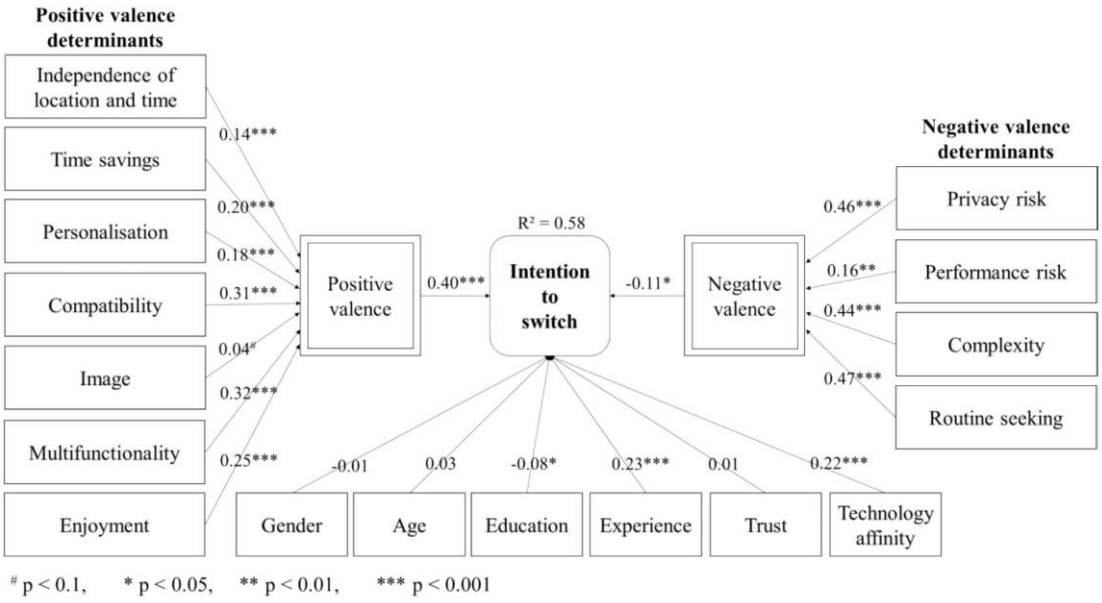

Figure 2. PLS results of the research model.

5 Discussion

5.1 Implications for theory and practice

Our research investigated the influence of *positive* and *negative valence* on the intention to switch from kiosk to mobile SST. For this reason, we developed a research model to capture the *positive* and *negative valence determinants* which are crucial for customers' intention to switch. Our work has several contributions to theory and practice. First of all, we developed a multidimensional research model allowing us to capture the influence of *positive* and *negative valence* on customers' intention to switch from kiosk to mobile SST. Thereby, we found that the *positive valence* (β=0.40, p=0.001) as well as the *negative valence* (β=-0.11, p=0.05) are both crucial for intention to switch (cf. Figure 2). We found that the *positive valence* is significantly more important than the *negative valence* (p<0.001). To date, the influence of positive and negative aspects on intention to switch has only been investigated by few studies in information systems research (e.g., Kim et al., 2006; Chang et al., 2014). While existing research focusses on switching intentions in social network sites (Chang et al., 2014) or between email services (Kim et al., 2006), we expand existing research by examining two of the most prevalent SST types, namely kiosk and mobile SST. The significantly stronger effect of the *positive valence* observed in our study is in contrast to Chang et al. (2014), who examine behaviour on social network sites and state that the influence of positive and negative aspects are similarly strong. It therefore can be assumed that the relative importance of positive and negative aspects varies depending on the context.

Second, we investigated – as one of the first – how the *positive* and *negative valence* are composed in the context of mobile SST. We found that the benefits *multifunctionality* (β=0.32, p<0.001), *compatibility* (β=0.31, p<0.001), and *enjoyment* (β=0.25, p<0.001) are the most important for the intention to switch while the relevance of *image* (β=0.04, p<0.1) as well as *performance risk* (β=0.16, p<0.01) are rather negligible. In literature to date, little is known about the compositions of the *positive* and *negative valence* for the intention to switch. Thus, in contrast to existing research which considers only few or even single determinants (e.g., Bhattacherjee and Park, 2014; Chang et al., 2014; Kim et al., 2006; Moore and Benbasat, 1991), we are the first trying to get an in-depth understanding of the multiplicity of the determinants composing the *positive* and *negative valence*. Regarding the few determinants considered in prior research, our findings confirm the strong positive influence of *enjoyment* on intention to switch (Dabholkar, 1996; Negahban and Chung, 2014). Further, they are in line with Moore and Benbasat (1991) who find *image* effects in IS adoption as being surprisingly low. The clear dominance of *multifunctionality*, *compatibility*, and *enjoyment* reveals that customers expect mobile SST to fit their lifestyle and to be convenient for managing their daily tasks. Thus, customers expect mobile SST to be a companion in every life situation. Further, the minor importance of *performance risk* clearly demonstrates a general trust in the new technology. More precisely customers presumably expect the technology to be mature and without functional risks (such as incorrect ticket download). The reason may be a general technology ubiquity in addition with a growing network coverage. Long Term Evolution (LTE), Wi-Fi (for instance in trains) and elimination of roaming fees lead to weaker perceptions of potential performance risks as the amount of possible connection errors decreases.

Third, we show that while prior *experience* with mobile SST favours the switch (β=0.23, p<0.001), this also applies for *technology affinity* (β=0.22, p<0.001). As previous studies on customer characteristics have shown that prior experience indeed plays a role for initial or repeat use intention of technologies (e.g., Cheung and Lee, 2010; Kim and Gupta, 2009; van der Heijden et al., 2003), we confirm this research stream but extend it by the customers' *technology affinity*. Surprisingly, neither *age* (β=0.03) nor *education* (β=-0.08, p<0.05) play a major role for switching from kiosk to mobile SST.

Our research has also several implications for practice. First, based on our findings, we highly recommend firms to recognize especially the benefits as the main driving determinants leading to an actual switch to mobile SST. Thus, firms should focus on further improving and promoting the benefits of their mobile SST, rather than justifying the disadvantages. Moreover, if companies generally aim at increasing their customer base, it apparently seems to be less effective to emphasize the disadvantages of possible competitors but rather to advertise and highlight their own advantages. Second, since mobile SST nowadays support users in nearly every situation of life, we strongly suggest practitioners to put particular focus on multifunctional, compatible and enjoyable SST features to meet customers' lifestyles. Otherwise, customers may reject the mobile SST and not switch from their habitually used SST. Further, as people are regularly exposed to mobile SST in their daily lives, they expect flawless functionality. Besides, companies do not need to address customers by age groups as customers of different ages do not display differences in their intention to switch.

5.2 Limitations

Although the study enables a deeper understanding of the determinants influencing customers' intention to switch to mobile SST, a number of limitations remain. Yet, together with the findings of this paper, our implications represent starting points for future research. First, the collected data was from one specific case and contained a large amount of answers from younger people which may limit the generalizability of our findings. However, since our survey was carried out in a real customer service setting, we are confident that our rich data set provides a solid foundation for testing the research model. Second, while the valence framework delivers a good basis for first insights in this topic, future research needs to include further aspects, such as computer self-efficacy, identity concepts and emotions which additionally play important roles in usage decisions. Third, our study did not differentiate between different functions and types of mobile SST but rather analysed mobile SST in general. We decided to do so in a

first step to prevent mixing distinct effects that may arise for different types of mobile SST. Yet, future research should examine variations of mobile SST.

6 Conclusion

Due to the ongoing proliferation of SST and the resulting autonomy of the customer in vast aspects of daily life, it is an imperative to differentiate between the different types of SST. While kiosk SST are widely used, also mobile SST are beginning to capture the market. Yet, enforcing customers to switch from kiosk to mobile SST can still be difficult due to routine seeking, privacy risks, or fear of complex user interfaces. As a result, users are locked into a status quo and do not switch to alternatives. Nevertheless, it can be advantageous for companies when their customers use the mobile SST as this enables them to collect valuable data on their customers. Hence, there is a need to better understand why customers switch from kiosk to mobile SST. Against this background, the aim of this paper was to gain a better understanding of the factors influencing the intention to switch from kiosk SST to mobile SST. We investigate the positive and negative determinants, which constitute the *positive* and *negative valence* of mobile SST as factors influencing the intention to switch. Our study expands existing research by outlining the particular importance of the *positive valence* for the customers' intention to switch, elucidating that concerns about potential disadvantages are rather low. With this in mind, the determinants *multifunctionality*, *compatibility*, and *enjoyment* clearly constitute the most crucial determinants, which shows that factors supporting "the mobile lifestyle" are appreciated most by the customers. By contrast, they see little importance in *performance risk*, which implicates a general trust in the new technology. Moreover, we examined that people who generally like using new technologies apparently rather tend to switching as compared to people with low *technology affinity*. Companies are therefore well advised to focus on highlighting the advantages of the mobile SST rather than justifying potential disadvantages in order to convince their customers to switch. Overall, our study is the first to combine *positive* and *negative valence determinants* as the fundamental aspects for customers' intention to switch to mobile SST and to compare their relative importance. With our work, we hope to contribute to a better understanding of customers' switching behaviour in the context of mobile SST. Furthermore, our theoretical and practical contributions serve as a proper starting point for future research on this exciting topic.

Appendix A – Questionnaire Items

Independence of location and time (IN) (developed based on Mallat et al., 2008)			
IN 1	Mobile SST eliminate the act of queuing.	IN 3	Using mobile SST is independent of location.
IN 2	Using mobile SST is independent of time.		
Time savings (TS) (adapted from Dabholkar, 1996)			
TS 1	I need a lot of time for using mobile SST.	TS 3	Using mobile SST allows me to save time.
TS 2	Using mobile SST is very quick.	TS 4	Using mobile SST reduces queuing time.
Personalisation (PE) (adapted from Xu et al., 2011)			
PE 1	Mobile SST can provide me with personalised services tailored to my needs.	PE 3	Mobile SST can provide me with more convenient services that I like.
PE 2	Mobile SST can provide me with additional information tailored to my personal interests.		
Compatibility (CO) (adapted from Moore and Benbasat, 1991)			
CO 1	Using mobile SST is compatible with all aspects of my life.	CO 3	Using mobile SST fits into my life style.
CO 2	I think that using mobile SST fits well with the way I like to live.		
Image (IM) (adapted from Venkatesh and Davis, 2000)			
IM 1	People around me using mobile SST have more prestige than those who do not.	IM 3	Using mobile SST is considered a status symbol among my friends.
IM 2	Using mobile SST enhances my image.		

Multifunctionality (MU) (adapted from Negabhan and Chung, 2014)			
MU 1	The multifunctionality of mobile SST meets my needs.	MU 3	The multifunctionality of mobile SST is adequate for accomplishing my experience.
MU 2	Mobile SST has all the functionality that I find necessary.	MU 4	I am satisfied with the multifunctionality of mobile SST
Enjoyment (EN) (adapted from Dabholkar, 1996)			
EN 1	It is enjoyable to mobile SST.	EN 3	It is pleasant to use mobile SST.
EN 2	It is exciting to use mobile SST.	EN 4	It is interesting to use mobile SST.
Privacy risk (PR) (adapted from Lu et al., 2011)			
PR 1	I would not feel safe providing personal private information over mobile SST.	PR 3	I would not feel secure sending sensitive information across mobile SST.
PR 2	I am worried about using mobile SST as other people may access my personal data.		
Performance risk (PF) (adapted from Lee, 2009)			
PF 1	Mobile SST may not perform well due to connection problems.	PF 3	Mobile SST may process data and service requests incorrectly.
PF 2	Mobile SST may not perform well due to technical problems.		
Complexity (CX) (developed based on Treviño et al., 2000 and Järveläinen, 2007)			
CX 1	I assume that much individual information is needed to use mobile SST.	CX 3	I presume using mobile SST to be a complicated incident.
CX 2	My information needs to understand the individual steps of mobile SST may be high.		
Routine seeking (RS) (adapted from Oreg, 2003)			
RS 1	I prefer having a stable routine to experiencing changes in my life.	RS 3	I like to do the same old things rather than try new and different ones
RS 2	I generally consider changes to be a negative thing.	RS 4	I like to experience novelty and change in my daily routine.
Intention to switch (IS) (adapted from Chang et al., 2014)			
IS 1	I am considering switching to mobile SST.	IS 3	I am determined to switch to mobile SST.
IS 2	The chance that I switch is high.		
Trust in mobile SST (TR) (adapted from Kim et al., 2009)			
TR 1	Mobile SST always provide accurate service.	TR 3	Mobile SST always provide safe service.
TR 2	Mobile SST always provide reliable service		
Technology affinity (TA) (adapted from Venkatesh et al., 2003)			
TA 1	I use a lot of new technologies in my everyday life.	TA 3	It is pleasant for me to deal with new technologies.
TA 2	I feel good about using new technologies.		

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2.3 Paper 3: Can Money Convince You? – Monetary Incentives and Mobile Self-Service Technologies

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Can Money Convince You? – Monetary Incentives and Mobile Self-Service Technologies

Abstract. Mobile self-service technologies (SST) pervade evermore facets of people's everyday lives. While they bear several advantages for customers, they also offer companies the opportunity to collect valuable customer data. However, customers' switch to mobile SST sometimes still turns out to be difficult. Yet, people's participation is crucial for the success of mobile SST. Against this backdrop, monetary incentives have been identified as effective motivators to influence people's behavior and therefore may bear enormous potential to convince customers to switch to mobile SST. Since recent literature does not provide comprehensive information on monetary incentives in the context of mobile SST, we investigate this aspect more in-depth. We outline the potential of price discounts for convincing customers to switch to mobile SST and show that lower experienced customers may be convinced by one-time vouchers. Our study helps to gain a better understanding of monetary incentives in the context of mobile SST.

Keywords: Mobile Self-Service Technologies, Monetary Incentives, Switching Behavior.

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1 Introduction

Digital technologies have increasingly permeated various facets of our social and economic lives. Online check-in for flights, mobile ticketing via smartphone, or self-checkout systems in supermarkets are taken for granted in today's fast-paced world. Along with this development, self-service technologies (SST) have become more and more prevalent in recent years. SST are technological interfaces "that enable customers to produce a service independent of direct service employee involvement" [1]. Among them, in particular mobile SST are gaining evermore importance. This is paralleled by the fact that the worldwide number of mobile device users has grown to 5.035 billion in 2017, with the latest billion users being added in just the last four years. Hence, two-thirds of the world's population use mobile devices, such as smartphones or tablets [2]. Mobile SST (e.g., applications on mobile devices) are a subdivision of internet SST. Whereas internet SST encompass apart from mobile SST for instance also computers, mobile SST provide customers with significant benefits, for instance pervasive and universal access to information and services, personalized services due to data tracking (e.g., GPS data), and in particular enhanced flexibility and mobility through independence of location and time and thus improved time management [e.g., 3]. Although people may be concerned about privacy risks or data tracking, the mobile lifestyle is continuing to occupy people's everyday lives, among others due to these advantages. A well-established example deriving from practice is the German public transportation company "Deutsche Bahn". They offer different well-accepted SST options, among them the application "DB Navigator". It allows customers, among others, to simultaneously catch up on real-time travel information and purchase tickets and thus to travel completely without the need to use another service delivery method. Hence, it spares the customer the need to go to a certain place for information or ticket purchase (such as the service desk or the computer at home). Besides, mobile SST are of particular interest for companies. As opposed to kiosk SST (e.g., automated teller machines) where customers act anonymously as they do not necessarily or automatically reveal personal or GPS information, mobile SST offer companies the opportunity to collect valuable data on their customers as their information can be tracked automatically in the background. Thereby, they can gain information on preferences and behavior patterns, which allows for using resources more wisely. This is why companies favor their customers to switch from anonymous SST, such as kiosks, to mobile SST. A key factor for the success of mobile SST lies in the people's participation [4]. However, potential consumers may not adopt them due to for instance switching costs or privacy concerns [5]. Hence, it remains questionable how people can be motivated to participate. Yet, to influence people's behavior, incentives are a frequently used approach. They could help to overcome concerns and attract a larger number of participants as they lead to more effort and better performance [6]. In particular monetary incentives have been proven to be an effective means in different environments [e.g., 7, 8]. Yet, although the impact of monetary incentives has been explored in various contexts and although they may open up new opportunities to enhance mobile SST participation, they have not been addressed in the context of mobile SST to date. Therefore, the aim of this paper is to explore monetary incentives

in the context of mobile SST to get first insights into the potential of monetary incentives in this environment and gain a better understanding thereof. On behalf of a case study at German train stations, we investigate different kinds of monetary incentives and their relative importance for convincing customers to switch from kiosk SST, which to date has been the prevailing kind of SST at train stations, to mobile SST, as comparably novel kind of SST. Moreover, we analyze the influence of customers' prior experience with mobile SST to gain an understanding of differences between customer groups with different experience levels. Finally, we investigate the necessary monetary amount to convince customers to switch to mobile SST. The research questions driving this study are: *1) Which monetary incentives are relevant for customers' switch to mobile SST? 2) How does their relative importance vary with different experience levels?*

The remainder of the paper is as follows: Section 2 provides an overview of the related literature. In Section 3, we describe the research method. Afterwards, we present the results of our analysis in Section 4. In Section 5, the results are discussed and theoretical and practical implications are presented. Finally, we conclude the paper with a brief summary in Section 6.

2 Theoretical Background

SST are technological interfaces that enable customers to access services without physical interaction with a service employee [9]. They can be differentiated based on the technology used, namely interactive kiosk, internet (incl. mobile), and interactive voice response. Among them, the internet-based SST type is the most prevalent [1].

2.1 Mobile SST and Switching Behavior

Mobile SST encompass services operated on a mobile device, such as both voice and data services, for instance, roaming, SMS and MMS, video streaming, or location-based services [10].They are a subdivision of internet SST with the latter encompassing apart from mobile SST for instance also computers. The benefits of mobile SST can be summarized in four factors, namely ubiquity, convenience, localization, and personalization. These benefits allow for more compatible, personalized, and uninterrupted services [11]. Yet, from a technological point of view, mobile SST harbor some disadvantages. One disadvantage is performance risk, for instance due to limited battery power and processing abilities [12]. Further, they may have complex user interfaces due to smaller displays and input buttons leading to a fear of usage [12, 13].Another major issue are privacy concerns, that is to say the fear of potential loss of control over personal information [14]. Reacting to these concerns, mobile device providers have constantly been improving the devices' privacy settings to give the user a feeling of safety. It is, for instance, possible to restrict access to location and contacts, photos, calendars, reminders, Bluetooth sharing, as well as to social media accounts. The challenge is to accomplish two tasks - consider privacy concerns and put measures

in place to mitigate those concerns – to reach a broad user acceptance of mobile SST [15].

User acceptance is widely considered as the most important factor for determining the success of an information system project. It can be defined as "the demonstrable willingness within a user group to employ information technology (IT) for the tasks it is designed to support" [16]. The Technology Acceptance Model (TAM) is the most prevalent model for predicting IT acceptance [17]. It derives from the Theory of Reasoned Action, which conveys that beliefs influence intentions, and intentions in turn influence one's actions [18]. Whereas the factors leading to adoption have been investigated in depth by technology adoption research, the individuals' resistance to technologies has drawn much less attention so far [e.g., 5]. Whenever new technologies are implemented in organizations, customers can develop resistance behavior against them, caused by, for instance, switching costs and perceived threats. Therefore, before switching to an alternative, individuals evaluate relative costs and benefits of the change, which illustrates that switching behavior is determined by the perceived advantages and disadvantages of a technology [5].

2.2 Intrinsic and Extrinsic Motivation and Monetary Incentives

Human behavior is triggered by motivation. Motivation can be classified as intrinsic and extrinsic [19]. Intrinsic motivation relates to doing something because it is inherently enjoyable or interesting. Consequently, it is not easy to manipulate. Extrinsic motivation on the other hand makes individuals do something because it leads to a separable outcome and many strategies can potentially stimulate it [19]. Existing literature shows that there are two effective strategies for promoting human's motivations in different contexts, namely monetary incentives and social comparison [8]. Monetary incentives such as cash, price discounts, vouchers, or redeem points, are effective in reinforcing extrinsic motivation in many respects. Economists conclude that higher monetary incentives will lead to more effort and better performance [6]. The standard (simple) economic principal-agent theory states that monetary incentives increase the marginal benefit of performing which consequently raises the performance and is also called the "standard price effect" [6]. For instance Lazear [20] finds monetary incentives to significantly increase worker effort. Eyting et al. [21] state that monetary incentives significantly increase the number of organ donors and Gneezy et al. [6] find that monetary incentives may improve student performance, prosocial behavior, and lifestyle habits. Moreover, they are used to motivate people to participate in online communities [22]. Burtch et al. [23] for example find that monetary incentives can motivate consumers to write more online reviews and Becker et al. [22] show that monetary incentives can increase the adoption of online communities. However, to the best of our knowledge, research on monetary incentives has not been conducted in regard of mobile SST. Yet, the literature stream encompassing monetary incentives in the aforementioned contexts may serve as a basis for this study and shed some lights to this research.

Yet, researchers find that monetary incentives may have two kinds of effects: the direct price effect, or "crowding in effect", which leads to the intended behaviors, and

an indirect psychological effect, which works in an opposite direction and crowds out the intended behaviors This is the so called "crowding out effect", or "over- justification effect" [24]. The classical example is given by Titmuss [25] who shows that paying people for blood donation may result in less people wishing to donate. Moreover, while monetary incentives may work for some people, they do not for others. For instance, there can be differences between male and female [6]. Further research finds they work only for top tier students or for employees with high initial intrinsic motivation [26].

In summary, monetary incentives have been identified as one of the most important means to prompt individuals' behaviors [7, 27]. Yet, to the best of our knowledge, their potential has not been investigated in the context of mobile SST nor in a comparable context. However, there are increasing calls to better understand them and they bear enormous potential for customers' participation in mobile SST. Against this backdrop and as the mobile lifestyle is becoming ever more ubiquitous in our everyday lives, it is crucial for companies to get a better understanding of how to motivate their customers to use mobile SST. Therefore, the aim of this paper is to gain a better understanding of monetary incentives in the context of mobile SST.

3 Research Method

3.1 Measurement Development

As monetary incentives in the context of mobile SST have not been subject to research to date, we adapted well established monetary incentives from other research streams and adjusted them to the mobile SST context. In detail, they derived from research on online communities and online reviews [23, 28–30], reward systems [31, 32] and medication adherence [33, 34]. We identified four monetary incentives of interest for mobile SST, namely *cash payments to customers*, *vouchers to purchase specific goods or services*, *price discounts*, and *loyalty programs including reward points*. The underlying literature as well as descriptions of each incentive are depicted in Table 1. In addition to those incentives deriving from literature, we added the incentive *special offers* which cannot be found in the literature to date. However, the opportunity to get special offers (e.g., campaigns such as "buy two tickets get one free") that are only offered in the mobile SST may constitute an important incentive, which may not be neglected.

Table 1. Monetary incentives in the context of mobile SST

Incentive	*Description*	*References*
Cash payment	Receipt of a one-time cash payment when switching to the mobile SST	Burtch et al. (2017), Cabral and Li (2015), Tulsky et al. (2004), Wang et al. (2012)
Voucher	Receipt of a one-time voucher for specific goods or services when switching to the mobile SST	Burtch et al. (2017), Barnett et al. (2009), Tulsky et al. (2004)

Price discounts	Access to price discounts when using the mobile SST	Burtch et al. (2017), Li (2010)
Loyalty program	Participation in a loyalty program where reward points can be collected and exchanged	Deci (1971), Son et al. (2016), Wang et al. (2012)
Special offers	Access to special offers that are only available in the mobile SST	n/a

3.2 Data Collection

To investigate the identified monetary incentives, this study adopted a field survey methodology for data collection. A questionnaire consisting of three sections to capture the incentives was administered. In Section 1, respondents were asked to rank order the monetary incentives based on their desirability level toward the incentives. In Section 2, the importance level of the incentives was asked on behalf of Likert scales ranging from strongly disagree (1) to strongly agree (5). In Section 3, the respondents were asked to quote a monetary amount (in Euro) that would be necessary to convince them to switch from kiosk to mobile SST. No amounts were predetermined, hence they could answer unrestrictedly. Finally, demographic items were included. The design of the survey followed standard instrument construction procedures [35]. Whenever possible, we adopted existing instruments from prior research to ensure reliability and validity of the measures. All incentives were adapted to the context of mobile SST. The questionnaire is provided in the appendix.

A pretest with 14 people with different demographics was conducted to evaluate the questionnaire and to ensure its comprehensibility. It did not suggest any methodological or systematic lacks and it solely led to minor revisions regarding wordings. We focused on two kinds of SST in this study, namely kiosk SST and mobile SST. While kiosk SST give the customers the feeling of acting anonymously (as they do not necessarily have to reveal personal or GPS information), mobile SST enable collecting customer data automatically in the background which may give the customer a feeling of insecurity. Hence, the focus on kiosk and mobile SST enabled us to analyze the impact of monetary incentives on the switch between SST with different degrees of anonymity, which may elucidate the distinctiveness of mobile SST as compared to other SST. To receive meaningful results, the survey was conducted at two train stations in Germany as they offer well-accepted kiosk SST as well as mobile SST. The interviewers answered the questionnaires together with the respondents to ensure a correct understanding of the items and respond to potential ambiguities. The data was collected during six weeks (in October and November 2017) on different working days to cover a broad range of customers with varying demographic variables. Of the 406 surveys collected, 346 usable responses (85.22%) remained for data analysis after removing deficient answers. Table 2 lists demographic information of the respondents.

Table 2. Demographic information of the respondents (n=346)

Measure	***Items***	
Gender	Male (n=166; 47.98%)	Female (n=180; 52.02%)

Age	14-19 (n=53; 15.32%) 20-29 (n=132; 38.15%) 30-39 (n=53; 16.18%)	40-49 (n=27; 7.80%) 50-59 (n=56; 16.18%) >59 (n=22; 6.36%)
Education	University (Bachelor, Master) (n=153; 44.42%) Secondary education (n=121; 34.97%)	Elementary school (n=69; 19.94%) No degree (n=3; 0.87%)
Mobile SST usage	Never (n=17; 4.91%) Rarely (n=57; 16.47%) Sometimes (n=98; 28.32%)	Often (n=126; 36.42%) Always (n=48; 13.87%)

4 Results

To get first insights into the topic of monetary incentives in the context of mobile SST, each incentive was regarded individually without considering possible dependencies amongst them. We decided to do so in a first step to gain a first understanding of the individual incentive's potential in this context. Against this backdrop, the results of Section 1 reveal that *discounts* and *cash payment* are among the most important monetary incentives for the switch to mobile SST as they rank most often the top two incentives. 73.70% of the respondent vote for *discounts* or *cash payment* as rank 1, while only 13.87% see them as the least important incentives (cf. rank 5). The lower ranks are dominated by *special offers*, *voucher*, and *loyalty program*. Yet, *special offers* are represented in each rank with approximately the same share of roughly 20% (cf. Fig. 1).

Figure 1. Ranking of monetary incentives

Due to the "Rank Aggregation Problem" [36] there is no satisfying approach to aggregate individual rankings to one major ranking that may depict the importance of the incentives more obviously. Although there are approaches that aim at solving this problem [e.g., 37], there is no satisfying approach for the purpose of this study. Therefore, we additionally investigated how much importance the respondents attach to each incentive by utilizing Likert scales ranging from strongly disagree (1) to

strongly agree (5) (cf. Section 2). To compare the importance of the incentives, we calculated the mean ($\bar{x}$) for each incentive. This used to be a controversial measure for Likert scales, but this controversy was comprehensively reviewed [38]. It was shown that parametric tests not only can be used with ordinal data, such as data deriving from Likert scales, but even that they are in general more robust than nonparametric tests. Thus, parametric tests, such as the mean, are sufficiently robust to bear largely unbiased answers when analyzing Likert scale responses. Against this background, the results reveal that *discounts* ($\bar{x}$=4.01) clearly dominate, followed by *special offers* ($\bar{x}$=3.30), *cash payment* ($\bar{x}$=3.21), and *voucher* ($\bar{x}$=3.06) that are on a similar level. By far the least important incentive is *loyalty program* ($\bar{x}$=2.41) (cf. Table 2). The comparisons of the means based on the t-statistic [39] revealed that the differences between *discounts* and all other incentives (p<0.001) as well as the differences between *loyalty program* and all other incentives (p<0.001) are significant.

Table 3. Means for different customer groups (maximum values are bold)

	Cash payment	*Voucher*	*Discounts*	*Loyalty program*	*Special offers*
Mean (all customers)	3.21	3.06	**4.01**	2.41	3.30
Mean (lower experience)	3.16	3.16	**3.97**	2.24	3.31
Mean (higher experience)	3.25	2.95	**4.06**	2.58	3.29

It is to presume that customers learn from their experiences with mobile SST and appreciate different incentives depending on their experience level [40]. Accordingly, to gain deeper insights into how the relative importance of the individual monetary incentives varies with different mobile SST experience, we distinguished two groups: First, customers with lower experience, i.e. customers who have never used mobile SST or use them rarely or sometimes (N_1=172; 49.71%). Second, customers who use them often or always and thus with a higher experience level (N_2=174; 50.29%). The comparison of the means of these customer groups reveals that first of all *discounts* is the most important incentive independently of the experience level. However, when comparing customer groups considering their different experience levels, the results show that *voucher* has significantly more importance for customers with lower experience ($\bar{x}$=3.16) as compared to customers with higher experience ($\bar{x}$=2.95). As opposed to this, *loyalty program* gains importance for higher experienced customers ($\bar{x}$=2.58) as compared to customers with lower experience ($\bar{x}$=2.24). The differences regarding the importance of *cash payment*, *discounts*, and *special offers* are unremarkable. The apparent differences concerning the importance of *voucher* (t=1.73; p<0.05) and the importance of *loyalty program* (t=3.02; p<0.01) are significant. Regarding demographics, no further conspicuities between demographic information (i.e., gender, age, education) and the individual incentives are discovered.

In Section 3, the respondents were asked to quote a monetary amount that would be necessary to convince them to switch from kiosk to mobile SST. This is in particular interesting regarding lower experienced customers (N_1=172) as they still bear the potential to be convinced. The results reveal that the majority (75.74%) would be

satisfied with a monetary amount up to 50 Euros. Among them 7.35% would switch costless. Only the minority (24.26%) would demand for an amount higher than 50 Euros.

5 Discussion

While monetary incentives have been recognized as among the most important motivators to improve effort and performance, there is a lack of research on monetary incentives in the context of mobile SST. Against this background, the aim of this paper is to gain a better understanding of monetary incentives in the context of mobile SST. More specifically, we investigate different kinds of monetary incentives and their relative importance for convincing customers to switch from kiosk to mobile SST. This work has several contributions for theory and practice.

5.1 Implications for Theory and Practice

First, we propose monetary incentives that may be relevant for the switch to mobile SST. To the best of our knowledge, we are the first to investigate different kinds of monetary incentives in this context. Thereby, we identify monetary incentives that have been examined in other contexts and adapt them to the context of mobile SST. We identify five monetary incentives of interest, namely *cash payments*, *vouchers*, *price discounts*, *loyalty programs*, and *special offers.* By so doing, we extend existing research on monetary incentives to a new emerging research area that is increasingly gaining interest. We shed light into which kinds of monetary incentives can serve as motivators for customers to switch from other SST, such as kiosks, to mobile SST and improve the general understanding of research on monetary incentives.

Second, we deliver first insights regarding the relative importance of the individual monetary incentives for customers' switch from kiosk to mobile SST. We find that *discounts* is by comparison clearly the most important incentive – independent of the customers' experience level. This is in line with prior studies' findings that discounts increase customers' participation [29, 30]. The introduction of a *loyalty program* on the other hand seems only of little interest. Interestingly, when considering customers' different experience levels with mobile SST, the attractiveness of the latter increases for higher experienced customers. It goes without saying that this is reasonable as customers using mobile SST more often can collect more reward points which in turn can be exchanged for other goods or services. For this part, our findings comply with Son et al. [31] who find that reward points in the context of apps enhance the existing users' engagement level. In fact, our results show that lower experienced customers do not valuate this advantage. Yet, for them the attractiveness of a *voucher* is higher instead. This may be explained in such that lower experienced customers are not sure if they will indeed continue using the mobile SST or quit again after a while which makes a one-time *voucher* much more interesting than a *loyalty program.*

Third, we show that to convince customers with lower experience to switch to mobile SST, a monetary amount up to 50 Euros would be appropriate for three quarters

of the respondents. Only the clear minority would switch costless. Interestingly, studies on online reviews state that monetary incentives already had considerable effects although the amounts offered per review were quite small (between 0.50$ and 2$) [30]. In fact, the monetary threshold leading to a switch to mobile SST could have been expected to be rather low in a world where people grow up with mobile technologies becoming an integral part of daily life. However, this elucidates that even customers who do not use mobile SST regularly are not averse from doing it. An explanation can be that people nowadays have gotten used to being confronted with new technologies, which they finally end up adopting. Against this backdrop, a general trust in new technologies, such as mobile SST, can be assumed. This complies with Lu et al. [41] who find that customers have general initial trust in mobile payment services which positively influences their intention to use them. Hence, the more a person is exposed to a technology in various situations in life, the more the technology is seen as common. This is in line with the trust transfer theory, which states that customer trust accumulated over time in internet services may influence customer trust in mobile-based services due to their similar nature [41].

For practice, this study shows that it is highly recommendable for firms to invest in offering monetary incentives in the context of mobile SST. This may ensure that the introduction of the mobile SST is effective and in fact profitable for the company. The advantages mobile SST comprise for companies are manifold: they allow to acquire new customers, enhance customer loyalty, convey an up-to-date image in times of digitalization, enable data collection for market research, and allow for location and time independent as well as targeted marketing as reaction to customer interactions and analysis of customer data. Regarding cost-effectiveness considerations, these benefits may on the long term well exceed the costs of investigating in monetary incentives. Moreover, although customers nowadays expect companies to offer mobile SST as service delivery alternative due to the fact that the digital lifestyle increasingly invades people's lives, this does not automatically imply that they will really make use of them. However, monetary incentives can well support companies to convince users who may reject the mobile SST at the beginning, in order to reach profitable usage rates. By knowing which monetary incentives are most effective, firms can focus on them and utilize them efficiently. In that manner, it is recommendable to further target companies' advertising by publicly communicating the monetary incentives they offer and thereby aim to increase the customers' awareness of the existence of these incentives. To attract lower experienced customers, firms should in particular focus on accentuating the opportunity of getting a voucher when switching to the mobile SST. Apparently, this could help to convince even more customers to use it. In addition, the opportunity of becoming member of a loyalty program is a further important factor to be highlighted (for instance via advertising) in order to maintain customers that are already using the mobile SST and enhance customer retention. This loyalty program can further help companies to tie their customers closer to the company as they will want to exchange collected reward points before they possibly expire. Hence, they may exchange them for a service or product of the company instead of going to a competitor.

5.2 Limitations

Although the study enables a deeper understanding of monetary incentives in the context of mobile SST, a number of limitations remain which, together with the findings of this paper, may represent starting points for future research. First, we did not differentiate between different types of mobile SST but rather analyzed mobile SST in general. We decided to do so in a first step to ensure a consistent understanding and to prevent mixing distinct effects that may arise for different types of mobile SST. Yet, future research should examine variations of mobile SST types in order to substantiate these findings. Second, our study solely considered monetary incentives. Further, it did not analyze the distinct impacts and interactions of the individual monetary incentives but rather derived descriptive findings in order to give first insights into this topic. However, our study may serve as a good basis for further research that could conduct deeper analyses of the functionalities and interplays (e.g., by structural equation modelling). Moreover, the data derives from a survey in one specific context. Therefore, the findings may not be representative for the totality of mobile SST users. However, since the survey was carried out in a real customer service setting, we are confident that it provides a good first step towards a more profound understanding of monetary incentives in the context of mobile SST.

6 Conclusion

Due to the rapid evolution of mobile SST and the resulting autonomy of the customer, it is important for companies to understand how customers can be convinced to participate in mobile SST. Monetary incentives are a frequently used approach to influence peoples' behavior and therefore could help to attract a large number of participants. Against this background, the aim of this paper was to gain a better understanding of monetary incentives in the context of mobile SST. We identified different kinds of monetary incentives and analyzed their relative importance for mobile SST. Hence, the study expands existing research by proposing and investigating monetary incentives that may help firms to convince their customers to switch from the popular kiosk SST to the comparably new mobile SST. The results elucidate the particular role of discounts, which among all monetary incentives appears to be the most important incentive for mobile SST. We furthermore analyzed how the customer's prior experience modifies the results and found that for people using mobile SST more often, loyalty programs gain attractiveness. Importantly, this is not applicable for customers with lower experience: they prefer vouchers to buy specific goods or services instead. Overall, this study delivers first insights in the relative importance of different kinds of monetary incentives for the switch from kiosk to mobile SST. With our work, we hope to contribute to a better understanding of monetary incentives in the context of mobile SST and that the theoretical and practical contributions serve as a proper starting point for future research on this exciting topic.

Appendix

Questionnaire

Description of mobile self-service technologies (SST): Mobile SST enable direct access to services (such as ticket purchase) without the necessity of going to a physical terminal (e.g., a self-service kiosk) or a service employee. The access to a service takes place via an application on a smartphone or a tablet. SST are widely used for travel information and ticketing (e.g., for trains, flights, or busses) as well as for banking. While kiosk SST are widely accepted, at times a certain distrust regarding mobile SST remains. However, monetary incentives may help to overcome this hesitance. Against this backdrop, the purpose of this questionnaire is to examine which monetary incentives may convince you to switch from kiosk to mobile SST.

Section 1

Please rank order the following monetary incentives based on your desirability level toward the incentives with number 1 being the most important and number 5 being the least important monetary incentive for you:

- Receiving a one-time **cash payment**
- Receiving a one-time **voucher** for certain goods or services
- **Discounts** (e.g., rebates on ticket prices)
- The opportunity to participate in a **loyalty program**, in which reward points can be collected that can be exchanged (e.g., in a ticket)
- **Special offers** that are only available via the mobile SST

1	
2	
3	
4	
5	

Section 2

Please decide for the following statements how much it would influence you to switch to the mobile SST.

	Strongly disagree				***Strongly agree***
Monetary incentive	1	2	3	4	5
Receiving a one-time cash payment influences me strongly.	☐	☐	☐	☐	☐
Receiving a one-time voucher for certain goods or services influences me strongly.	☐	☐	☐	☐	☐
Discounts (e.g., rebates on ticket prices) influence me strongly.	☐	☐	☐	☐	☐

The opportunity to participate in a loyalty program, in which I can collect reward points that can be exchanged (e.g., in a ticket), influences me strongly.	☐	☐	☐	☐	☐
Special offers that are only available via the mobile SST influence me strongly.	☐	☐	☐	☐	☐

Section 3

Which amount of money (in average) would convince you to switch to the mobile SST (in Euro)?	EUR

General information

Gender: ☐ Male ☐ Female

Age: ☐ 14-19 ☐ 20-29 ☐ 30-39 ☐ 40-49 ☐ 50-59 ☐ >59

Education: ☐ University (Bachelor, Master) ☐ Secondary education
☐ Elementary school ☐ No degree

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3. Research on Enterprise Social Networks

3.1 Paper 4: The Blessing of Giving: Knowledge Sharing and Knowledge Seeking in Enterprise Social Networks

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THE BLESSING OF GIVING: KOWLEDGE SHARING AND KNOWLEDGE SEEKING IN ENTERPRISE SOCIAL NETWORKS

Research

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Abstract

Whereas more and more companies use Enterprise Social Networks (ESN) for internal knowledge management, there is still a lack of understanding how employees communicate their knowledge in ESN to support their colleagues. We approach this gap by analysing users' roles and knowledge exchanging behaviours in a rich data set comprising more than two years of ESN usage. We identify three user roles, namely givers, takers, and matchers, regarding knowledge sharing and seeking behaviour and analyse their position in the organisational hierarchy. By applying means of Social Network Analysis, we contribute to a clearer picture of the significant role of givers and confirm findings of other studies that the majority of users behave as takers. Generally, our findings help to come to a more refined understanding of ESN usage and its role in knowledge practices.

Keywords: Enterprise Social Network, Social Network Analysis, Knowledge sharing, Knowledge seeking.

1 Introduction

In recent years, many organisations have started implementing Enterprise Social Networks (ESN) to foster internal collaboration, communication, and knowledge-sharing (Aral et al., 2013; von Krogh, 2012). According to a recent study the worldwide ESN market revenue is expected to grow from $1.24 billion in 2013 to $3.5 billion by 2018 (Thompson, 2014). Many organisations have recognised the potential of ESN with respect to the creation of competitive advantage by serving as a driving force to build effective and efficient business (Riemer et al., 2015a; Turban et al., 2011) as well as the generation of social capital within organisations, for instance by enhancing an employee's reputation in the company (Riemer et al., 2015a; Wasko and Faraj, 2005). At the same time, there is an increasing demand to better understand the role and impact of these social technologies in knowledge practices like information seeking, knowledge sharing or expert finding (Bharadwaj et al., 2013; Herzog et al., 2013; Richter et al., 2013a; Richter et al., 2013b).

In this line of argument, there are calls to research different actor roles in ESN usage (Trier and Richter, 2015) to better understand the potential of ESN for knowledge transfer and the network structures that influence, for instance, information dissemination (Chau and Xu, 2012) and contribution behaviour (Zhang and Wang, 2012). However, social networking behaviour in ESN with respect to employ-

ees' knowledge practices, i.e. how users share and seek knowledge in ESN, is still widely unexplored. More specifically, analysing the users' reciprocities in terms of giving and taking knowledge within an ESN and their structural characteristics have not yet been subject of academic discussion.

Therefore, our objective in this paper is to investigate the knowledge exchanging behaviour of users in ESN. Based on a Social Network Analysis approach, we classify users with respect to their amount of sharing and seeking knowledge. Moreover, we analyse the structural characteristics of user groups in each category. In so doing, we consider two aspects for characterising the user categories: knowledge sharing and seeking behaviour in a knowledge base (i.e. wiki) as well as communication activities and connectedness between users. In so doing, we address the following research questions: 1) How can users be classified with respect to their knowledge exchanging behaviour in ESN? 2) How can users in the different categories be distinguished with respect to their structural position in the ESN and in the organisational hierarchy?

Our results indicate that the users who outstandingly contribute knowledge for other users in the ESN without receiving respective return are amongst the most connected users in terms of writing messages to and having social relationships with other users. We also find that the allocation of the users in the different categories changes within hierarchical levels which implies a change in some users' characteristics over time, depending on how long he or she is within one level.

From a theoretical perspective, our findings contribute to the development of a more refined understanding of ESN usage in knowledge-intensive work. From a practical point of view, our insights can help organisations to better understand the social networking behaviour of their employees and thereupon take measures to improve in knowledge exchange. Moreover, we suggest to and illustrate how to refine methodology, namely "Absolute Distance Measure" and "Relative Distance Measure" to identify user groups in ESN based on their knowledge sharing behaviour.

The remainder of this paper is structured as follows: In Section 2, we provide an overview of the existing literature on knowledge sharing and knowledge seeking in ESN. Section 3 describes the research method, the case setting, and the data collection and analysis process. In Section 4, we present the findings of our analysis of the dataset. In Section 5, we discuss implications and limitations of our work and provide directions for further research. Finally, we conclude with a brief summary.

2 Theoretical Background

2.1 Enterprise Social Networks

In recent years, organisations discovered the growing need of their employees to be connected through an internal network in terms of information exchange, easier expert finding, ideation or team coordination (DiMicco et al., 2008; Thom-Santelli et al., 2011). ESN can facilitate easy corporation-wide knowledge exchange without being subject to departmental or geographic boundaries (Aoun and Vatanasakdakul, 2012) and contribute to more open and participative communication practices (Denyer et al., 2011; Holtzblatt et al., 2010; Ip and Wagner, 2008). Meanwhile ESN are a crucial means for companies to stay competitive (Aral et al., 2013).

The increasing usage of ESN also led to an increasing scholarly interest. Prior research addressed amongst others the adoption of ESN in organisations (Overfeld et al., 2012), the development of relationships between employees (DiMicco et al., 2009; Zhang and Wang, 2012), and the potential benefits of ESN in the corporate realm, including expert finding, problem solving, work coordination, and opinion sharing (Brzozowski, 2009; Richter and Riemer, 2013; Thom-Santelli et al., 2011). Researchers also showed that ESN usage does not only affect company performance, but also the career paths of employees. For instance, Wu (2013) revealed that ESN transfer the network positions of employees over time and found significant correlations with job performance and job security. In addition, the emergent network structures of ESN can transform power relations and hierarchies (Bobsin and Hoppen, 2013). In this context, research shows that formal organisational hierarchies (Behrendt et al.,

2015) and the level of communication activity (Riemer et al., 2015b; Stieglitz et al., 2014) significantly influence ESN networking behaviour. Muller et al. (2012) examined how diversity influences collaboration, teaming, and innovation, and Matthews et al. (2013) aimed at understanding how leaders enhance the value of their communities. Other research (Herzog et al., 2015; Herzog et al., 2013; Richter et al., 2013a) analysed how the use of these technologies can be evaluated.

2.2 Knowledge sharing and seeking in Enterprise Social Networks

Sharing and demanding with others is deeply rooted in human nature. Every time individuals interact with others, they have to decide within the two extremes of whether to claim as much value as possible or contribute value without expecting anything in return (Grant, 2014). Over the past decades, social scientists have discovered that people differ tremendously in their preferences for reciprocity – their desired mix of giving and taking. Grant (2014) classifies people as givers (i.e. people who give more than they get), takers (i.e. people who get more than they give) and matchers (i.e. people who try to trade evenly). This framework helps us to differentiate between people with preferences for sharing knowledge or seeking knowledge and can serve as an important basis of our study.

There is an increasing demand to understand the behaviour of users in ESN (Koo et al., 2011; Kuegler and Smolnik, 2014), especially in respect of information diffusion (Stieglitz et al., 2014) and knowledge exchange in ESN (Ortbach and Recker, 2014; Recker and Lekse, 2015), since ESN influence information dissemination (Chau and Xu, 2012) and contribution behaviour (Zhang and Wang, 2012). In this context, research focuses in particular on exploring the individuals' rationales behind online knowledge sharing (e.g., Phang et al., 2009; Schroer and Hertel, 2009) and seeking (e.g., Kankanhalli et al., 2005; Wasko and Faraj, 2005; Zhang and Wang, 2012). Further studies investigate the relation between online sharing and seeking knowledge (Phang et al., 2009; Yan and Davison, 2013).

Concerning knowledge exchanging behaviour in networks, Wasko and Faraj (2005) analyse why some users contribute more than others. They identify four reasons: 1) users perceive an enhancement of their professional reputation, 2) they enjoy helping others, 3) they are structurally embedded in the network, and 4) they have experience which is worth sharing with others. In this context, Kankanhalli et al. (2005) find that knowledge self-efficacy and enjoyment in helping others significantly impact knowledge contribution to electronic repositories whereas the loss of knowledge power and image do not appear to have any impact. Moreover, a person's position in the network influences the decisions about his or her total contribution and also the allocation of his or her efforts on the platform (Zhang and Wang, 2012). Referring to the example of Wikipedia, Schroer and Hertel (2009) examine predictors of contributors' engagement and satisfaction and show that satisfaction of contributors is determined by perceived benefits, identification with the community, and task characteristics, whereas their engagement depends on their tolerance for opportunity costs and the experienced characteristics of their tasks which again is partially mediated by intrinsic motivation. Other studies argue that collaborative norms (Bock et al., 2006), identity management (Ma and Agarwal, 2007), and knowledge validation processes (Durcikova and Gray, 2009) also influence knowledge contribution. Prior research has shown that approximately 90% of online community members take over a passive role – they are so-called lurkers (e.g., Katz, 1998; Mason, 1999). Nonnecke and Preece (2000) found that lurking varies and can range from as much as 99% to a low of 1%. In another study they revealed that there are many reasons for lurking in online social communities (e.g. reluctance or usability problems) but many lurkers are no selfish free-riders (Nonnecke and Preece, 2001). Schneider et al. (2013) draw the connection between epistemic curiosity as personality trait and emotional-motivational state to lurkers' contribution behaviour in online communities and find that the psychology of curiosity generally holds great promise for research on online communities in information systems. Understanding users' knowledge exchanging behaviour is especially important with respect to ESN, as users largely differ in terms of their connectivity (e.g. number of friends), their communication activity (e.g. number of messages) as well as their frequency, volume, and quality of the user-generated content (Trusov et al.,

2010). Trier and Richter (2015) identify two different and interrelated actor roles as an explanation for uneven levels of user contributions to ESN. They call them discourse drivers and information retrievers as two mutually interdependent actors which together shape the dynamics of the online interaction. Moreover, Berger et al. (2014) find that users who add value to the organisation by sharing their knowledge in the ESN are amongst the best connected users and thus enable a more effective and rapid exchange of information between different working groups.

Research focussing on knowledge seeking on platforms addresses either knowledge seeking behaviour of individuals (Bock et al., 2006; Kankanhalli et al., 2005) or its relation to knowledge sharing (Phang et al., 2009; Yan and Davison, 2013). For instance, Kankanhalli et al. (2005) examine electronic knowledge repositories (EKR) that serve the purpose of storing codified knowledge for future reuse within companies and investigate potential antecedents to EKR usage for knowledge seeking. Their results reveal that EKR usage for knowledge seeking is influenced by perceived output quality, resource availability, and incentives. Moreover, knowledge seeking and knowledge contribution in online communities are influenced by different aspects of usability and sociability (Phang et al., 2009). For instance, ease of use and system reliability are considered as more important for usability when individuals seek knowledge, whereas tracking fulfilment is more important for usability when individuals contribute knowledge. In addition, Yan and Davison (2013) analyse the mediating role of an individual's intrinsic motivation for the behavioural transfer from knowledge seeking to knowledge contribution in knowledge management in Web 2.0 applications.

From a management perspective it is essential to know which users outstandingly contribute their knowledge, allowing others to benefit from their experience, and which users primarily acquire knowledge without contributing much themselves. Therefore, the aim of this paper is to 1) propose two methods to classify users based on their knowledge sharing and seeking behaviour as givers, takers, and matchers (cf. Grant, 2014) and 2) investigate their structural characteristics as well as their position in the formal organisational hierarchy.

3 Research Method

3.1 Setting

We approach our research objective with the case of the medical service unit (MSU) of the German Armed Forces (Deutsche Bundeswehr). MSU is composed of, amongst others, 2,700 medical officers and 1,600 trainee medical officers for military medicine, military pharmacy, veterinary medicine, and dental medicine. They are distributed amongst five major military hospitals in Germany, 37 German universities offering medical studies, and 200 other facilities. In 2009, MSU decided to implement an ESN, MSU-Net, with the following aims: (1) encouraging knowledge transfer and collaborative learning among colleagues, (2) creating a collaborative knowledge base, (3) improving the quality of education as well as the in-service training of new colleagues, and (4) strengthening the corporate identity and the networking of the employees. MSU-Net, which was launched in November 2010, enables the employees to become virtual friends, write messages to other users, and post blog entries which can be commented by others. To foster the knowledge transfer, MSU-Net also includes a knowledge base to which employees contribute publically available (scientific) content.

A preliminary analysis of the dataset showed a high amount of information available about the users' communication (i.e. written and received direct messages) and knowledge exchange behaviours (i.e. written, modified and read articles in the knowledge base) so that the dataset is ideal for our research objective. As the activities in the knowledge base deliver us information about users' write accesses (i.e. written and modified articles) and read accesses (i.e. read articles), we can see who shares and who seeks knowledge. This enables us to classify the users as people who predominantly give knowledge, people who predominantly take knowledge, or people who give and take to a relatively balanced extent.

3.2 Data collection and preparation

The dataset contains the users' military ranks which follow the formal organisational hierarchies of the German Armed Forces. In our case, the military hierarchies are divided into six levels: enlisted soldier (level 1), non-commissioned officer (NCO) (level 2), officer candidate (level 3), officer (level 4), staff officer (level 5), and general (level 6). During data export, all personal information (such as user names) was removed to guarantee confidentiality. The dataset, referring to the time period between November 2010 and February 2015, was supplied in table format. It contains, amongst others, information about each user's confirmed contact requests to other users (in the following referred to as "social relationships"), direct messages exchanged with other users (written and received messages) as well as written, modified, and read articles in the knowledge base in MSU-Net. Of the 2,941 users, 1,732 users have at least one social relationship (total number of social relationships: 7,679). Furthermore, the data contains 19,571 direct messages between two users. Read accesses as well as write accesses in the knowledge base were provided on a monthly base ranging from January 2013 to March 2015. 2,034 users were active in the knowledge base: among those, 114 users wrote at least one article, 152 users made at least one article modification. A total of 1,041 articles were authored, 5,577 modifications were undertaken. Altogether, we observe a total of 6,618 write accesses and 91,082 read accesses.

3.3 Data analysis

To classify the users of the ESN as givers, takers, or matchers we focus on their knowledge sharing and seeking behaviour in the knowledge base. Indeed, the knowledge base in MSU-Net was created to support the knowledge exchange among employees. On the one hand, it allows users to write and modify articles to share their knowledge with others; on the other hand it allows users to read articles from other users to acquire knowledge. Against this background, those users of MSU-Net are regarded as givers who outstandingly share their knowledge in the knowledge base thus enabling others to gain more knowledge. Takers are regarded as users who outstandingly seek knowledge to their own benefits, whereas matchers share and seek knowledge to a relatively balanced extent. To assess each user's amount of knowledge shared and acquired in the knowledge base, we focus on his or her number of write accesses and read accesses in total and for each of the observed periods (i.e. 2013, 2014 and 2015), respectively. On this basis, we classify them as givers (users whose relative amount of write to read accesses is comparably high), takers (users whose relative amount of write to read accesses is comparably low), and matchers (users with a comparably balanced amount of write and read accesses). Write accesses potentially reach multiple users whereas read accesses refer to only one single user. Indeed, the total number of read accesses is much higher compared to the total number of write accesses. Therefore, for further analyses we use a factor to weight the number of write accesses to enable 1:1 comparisons. For 2014, for instance, the total number of read accesses is 47,067 and the total number of write accesses is 3,001 and we used the factor 15.68 (= 47,067 / 3,001) for weighting. We define a "pure giver" as a user with no read but one or more write accesses and a "pure taker" as a user with no write but one or more read accesses. A perfect matcher is characterised by an equal number of weighted write and read accesses.

Based on his or her number of read accesses and weighted write accesses each user can be represented in a Cartesian coordinate system (cf. Figures 1 and 2). The x-axis refers to the user's number of read accesses; the y-axis refers to his or her number of weighted write accesses. Thereby, pure givers and pure takers are directly located on the y-axis or the x-axis, respectively; perfect matchers can be found on the bisectrix. In the following, we propose two different methods to classify a user as giver, taker, or matcher. Methodically, both methods are founded on users' Euclidean distance to the lines representing pure givers (cf. y-axis), pure takers (cf. x-axis), and perfect matchers (cf. bisectrix) in this Cartesian coordinate system.

The first method is based on whether a user u is closest to being a perfect matcher, to being a pure giver, or to being a pure taker, respectively. Therefore, we determine his or her Euclidean distance to

the bisectrix (see $d_M(u)$ in Figure 1), the y-axis (see $d_G(u)$ in Figure 1) and the x-axis (see $d_T(u)$ in Figure 1) and classify the user according to the minimum absolute distance. Thus, in the following this method is referred to as "Absolute Distance Measure". Figure 1 provides illustrative examples of users classified as giver, taker, and matcher, respectively.

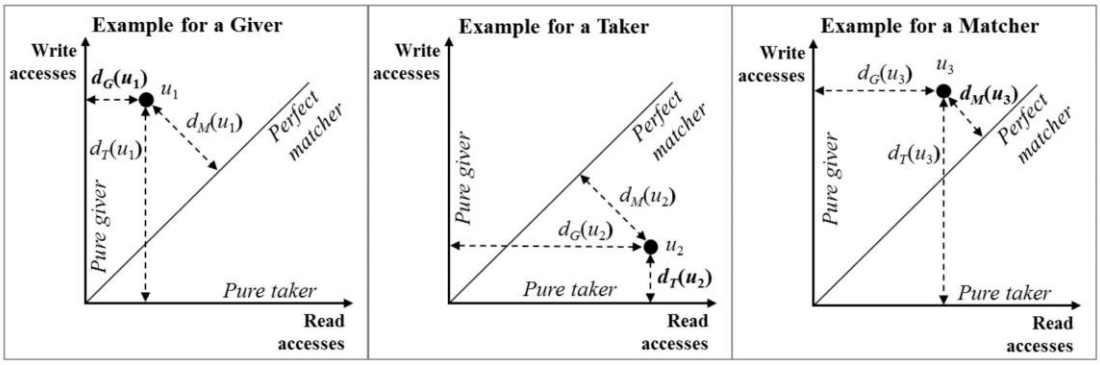

Figure 1. "Absolute Distance Measure" to classify users as givers, takers, or matchers.

The "Absolute Distance Measure" allows to classify a user independent from other users. To classify users as givers, takers, or matchers considering the knowledge exchanging behaviour of the other users of the ESN in comparison as well, we propose a second method, in the following referred to as "Relative Distance Measure". Thereby, we calculate each user's Euclidean distance (see $d_M(u)$ in Figure 2) to a perfect matcher in relation to his or her respective greatest possible Euclidean distance to a perfect matcher (see $d_{max}(u)$ in Figure 2). Here, $d_{max}(u)$ corresponds to the Euclidean distance of a perfect matcher to a pure giver or pure taker lying on a perpendicular to the bisectrix through user u. Putting $d_M(u)$ in relation to $d_{max}(u)$ allows us to compare users with high and low values of weighted write or read accesses. We then calculate the average of these relative distances. In our case, due to the large number of pure takers, this results in a value of 0.958 for all periods aggregated, 0.967 for 2015, 0.969 for 2014, and 0.953 for 2013. Based on this average and the respective user's individual relative distance to the perfect matcher, he or she is then classified as giver, taker, or matcher accordingly. Thereby, users whose individual relative distance differs less than average from the perfect matcher are classified as matchers; users whose individual relative distance differs more than average from the perfect matcher are classified as givers (more weighted write than read accesses) or takers (more read than weighted write accesses), respectively. Figure 2 provides illustrative examples of users classified as giver, taker, and matcher, respectively.

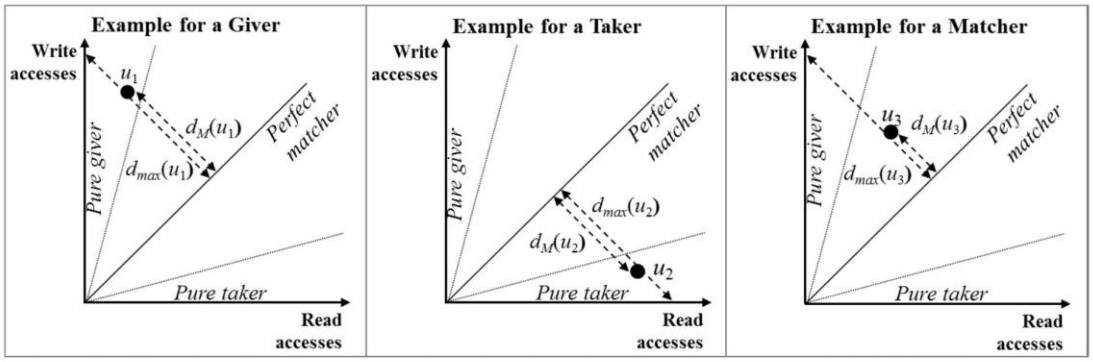

Figure 2. "Relative Distance Measure" to classify users as givers, takers, or matchers.

We applied both methods to all users in our dataset who participated (i.e. they had read and/or write accesses) in the knowledge base. The reason is that users who are only enrolled in the ESN without reading or writing in the knowledge base would influence the resulting allocations and finally distort our findings. Therefore, we conduct our further analyses focussing on the participating users only (2,034 for all periods, 690 in 2015, 1,673 in 2014 and 1,066 in 2013).

To investigate the structural characteristics of givers, takers, and matchers in ESN, we apply Social Network Analysis (SNA) (Wasserman and Faust, 2009). SNA was prior used in IS research to analyse for instance users' social networking behaviour in OSN and ESN (Behrendt et al., 2015; Krasnova et al., 2010), social capital as a result of the usage of OSN (e.g., Ellison et al., 2007), and the characteristics of key users in ESN (Berger et al., 2014). According to Freeman (2000, p. 350), SNA "involves theorizing, model building, and empirical research focused on uncovering the patterning of links among actors" by, for instance, quantifying the centrality of nodes within a network. In this context, there exists a variety of centrality measures, whereby the most common centrality measures are degree centrality, closeness centrality, and betweenness centrality (Freeman, 1979) as well as eigenvector centrality (Bonacich, 1972). Degree centrality assumes that a node with many direct connections to other nodes is central to the network. Closeness centrality expands the definition of degree centrality by focusing on how close a node is to all other nodes in the network. These nodes can, for instance, contribute to a fast exchange of ideas and information in the network. The idea behind betweenness centrality is that a node which is on many shortest paths between other nodes is central to the network. Users with high betweenness centrality are supposed to control the information flows in networks. Eigenvector centrality extends the logic of degree and closeness centrality and incorporates a node's connectivity in the whole network. Here, a node is more central to the network, if it is connected to other central nodes.

ESN can be represented as a graph with a set of nodes (users) and a set of edges (ties) linking pairs of nodes (Wasserman and Faust, 2009). The edges can be either directed or undirected and represent either social links like social relationships (social graph) or communication activities like messages among the users (activity graph) (Adamic and Adar, 2003; Bampo et al., 2008; Heidemann et al., 2010). We ground our research on both graphs in order to get profound insights into the structural characteristics of givers, takers and matchers in ESN. The social graph representing the social relationships comprises 2,941 nodes and 7,679 undirected edges (confirmed contact requests). The activity graph is inferred by the direct messages exchanged between a pair of users. It consists of 2,941 nodes and 4,830 directed and weighted edges (messages sent between two users). For the network analysis, we use Gephi (https://gephi.org/) to calculate degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality for each node of the social graph as well as of the activity graph. In addition, to gain deeper insights into the characteristics of givers, takers, and matchers with respect to their participation in the knowledge base, we also analyse their average numbers of written or modified articles (write accesses) and read articles (read accesses).

Finally, we also investigate the hierarchical positions of givers, takers, and matchers based on their level in the formal hierarchy of the organisation. To make our results transferable to a non-military organisational setting, we categorise levels 1 and 2 as lower hierarchical level, 3 and 4 as middle hierarchical level, and 5 and 6 as higher hierarchical level and compare them to common organisational roles based on the Administrative Order on the Position of the Military Superior (Bundesministerium der Verteidigung, 1956). Against this background, level 1 is the lowest level where the persons have no authority over others, whereas persons in level 2 can be compared to team leaders who give commands to level 1 employees with decision making power only in their own team. Level 3 can be compared to managers who lead a collection of teams (e.g., a department) and level 4 to business unit managers with responsibility for the management, training and staffing of a business unit or subdivision and authority over all lower levels of hierarchy. Level 5 can be compared to executive directors who are typically not involved in the daily business but lead divisions. They have authority over all lower levels and decide on strategic aspects. Level 6 can finally be compared to board members in

the top management that have authority over all lower levels. They fulfil representative and strategic tasks covering the entire organisation.

4 Results

4.1 Classification of givers, takers, and matchers

In this subsection, we classify the users of the ESN as givers, takers or matchers. Table 1 shows the resulting allocations of givers, takers and matchers for the Absolute Distance Measure as well as for the Relative Distance Measure and illustrates that for both measures the majority of the users are classified as takers. This holds for each of the observation periods.

	2015 (n = 690)		**2014** (n = 1,673)		**2013** (n = 1,066)	
	Distance Measure		**Distance Measure**		**Distance Measure**	
Category	**Absolute**	**Relative**	**Absolute**	**Relative**	**Absolute**	**Relative**
Givers	3% (19)	1% (4)	1% (22)	0% (0)	2% (22)	0% (0)
Takers	95% (655)	95% (654)	95% (1,595)	95% (1,586)	93% (995)	92% (979)
Matchers	2% (16)	4% (32)	4% (56)	5% (87)	5% (49)	8% (87)

Table 1. Allocation of givers, takers, and matchers.

Similar results can be observed for the aggregation of all periods (cf. Table 2): only 2% or 0% of all users are classified as givers, while more than 90% of all users are takers. The Bowker-Test (Bowker, 1948) reveals that the results of both methods, the "Absolute Distance Measure" and the "Relative Distance Measure", do not differ significantly ($\alpha = 0.05$). Therefore, as well as for reasons of clarity and the page length restriction we base our further analyses on users' classification based on the "Absolute Distance Measure" and for the aggregation of all periods.

Category	**Absolute Distance Measure**	**Relative Distance Measure**
Givers	2% (30)	0% (3)
Takers	94% (1,917)	93% (1,882)
Matchers	4% (87)	7% (149)

Table 2. Allocation of givers, takers, and matchers for all periods.

4.2 Structural characteristics of givers, takers, and matchers

To investigate the structural characteristics of givers, takers, and matchers in ESN, we first analyse how they are characterised with respect to their average numbers of write accesses and read accesses in the knowledge base as well as written and received direct messages, and social relationships.

The results (cf. Table 3) reveal that givers are very active users in the knowledge base of MSU-Net with an average of 141 written or modified and 464 read articles. Takers on the other hand write no articles on average but still read 31 articles. In average, matchers also read a lot of articles with 201 articles per user, whereas their write access is moderate with 23 written or modified articles per user. Concerning the communication in the ESN (i.e. direct messages), givers are very active with 151 written and 117 received messages per user, closely followed by matchers with 97 written and 99 received messages per user, while takers seem very passive in the ESN with only three written and four received messages. As far as social relationships are concerned, givers and matchers are amongst the best connected users, with on average 24 or 23 social relationships, respectively, whereas again takers only have 6 social relationships on average. Summing up the results of these analyses, givers are the highest contributors to the knowledge base by writing and modifying most articles per user. Moreover,

givers and matchers are amongst the most active users concerning communication activity and have most social relationships per user. Takers show opposite characteristics. They are amongst the least active users concerning their participation in the knowledge base as well as their number of social relationships and direct messages per user.

Category	Average no. of write accesses	Average no. of read accesses	Average no. of written direct messages	Average no. of received direct messages	Average no. of social relationships
Givers	141	464	151	117	24
Takers	0	31	3	4	6
Matchers	23	201	97	99	23

Table 3. User behaviour of givers, takers, and matchers.

To get further insights into users' connectedness in the ESN, we further analyse the centrality of givers, takers, and matchers in the social graph (i.e. social relationships based on confirmed contact requests) and the activity graph (i.e. communication based on direct messages). We apply closeness centrality, betweenness centrality, and eigenvector centrality to both graphs whose nodes represent all 2,941 users in MSU-Net (i.e. users who participate in the knowledge base as well as users who do not participate in the knowledge base). We do not consider users' degree centrality, since it represents the number of social relationships in the social graph and the number of direct messages in the activity graph respectively, which we already analysed before. We then rank all users in the network for each centrality measure in a decreasing order and classify them with respect to quartiles, with quartile 1 containing the 25% of the users with the highest and quartile 4 containing the 25% of the users with the lowest centrality scores. Tables 4 and 5 show for each category (givers, takers, and matchers) the percentage of the respective users belonging to the quartiles 1, 2, 3, and 4 (please note that all users of the ESN are considered for the ranking of the users and the quartiles for reasons of comprehensibility).

Category	Closeness Centrality Quartile				Betweenness Centrality Quartile				Eigenvector Centrality Quartile			
	1	2	3	4	1	2	3	4	1	2	3	4
Givers	77%	10%	10%	3%	83%	13%	0%	3%	73%	12%	10%	3%
Takers	30%	30%	22%	18%	29%	28%	25%	18%	30%	30%	22%	18%
Matchers	80%	14%	5%	1%	87%	11%	1%	0%	79%	14%	6%	1%

Table 4. Closeness, betweenness, and eigenvector centrality in the social graph.

The results for the social graph indicate that givers and matchers are very well connected. Indeed, more than 70% of givers and matchers belong to quartile 1 for closeness centrality, betweenness centrality, and eigenvector centrality. For instance, regarding betweenness centrality 83% of the givers and 87% of the matchers are in quartile 1, only 3% of the givers and 0% of the matchers are in quartile 4. This shows that nearly three out of four of the givers and matchers are amongst the best connected users in the social graph. Takers are in general less well connected (at most 30% in quartile 1). Again, this can be observed for closeness, betweenness as well as eigenvector centrality.

Similar to the social graph, givers and matchers are very well connected in the activity graph with more than 80% of the givers and matchers being in quartile 1 whereas takers again show lower centrality regarding all observed centrality measures. For instance, 83% of the givers and 82% of the matchers are in quartile 1 with respect to closeness centrality. In keeping with the social graph, at most 30% of the takers are in quartile 1.

Category	Closeness Centrality Quartile				Betweenness Centrality Quartile				Eigenvector Centrality Quartile			
	1	2	3	4	1	2	3	4	1	2	3	4
Givers	83%	10%	4%	3%	83%	10%	4%	3%	83%	10%	3%	4%
Takers	30%	27%	25%	18%	30%	27%	25%	18%	29%	28%	25%	18%
Matchers	82%	17%	1%	0%	84%	15%	1%	0%	87%	11%	2%	0%

Table 5. Closeness, betweenness, and eigenvector centrality in the activity graph.

In summary, the results underline that givers and matchers are better connected than takers in terms of social links (cf. social graph) and communication activities (cf. activity graph) in the ESN. This holds for all analysed centrality measures. Taking also into consideration that givers are amongst the most active users who share most knowledge by writing most articles in the knowledge base, they can be identified as most important users for distributing and sharing knowledge in ESN.

4.3 Hierarchical levels of givers, takers, and matchers

To get further insights into the representation of givers, takers, and matchers in the hierarchy of organisations, we finally investigate the allocation of each user category in the higher, middle, and lower hierarchy.

As depicted in Figure 3, the majority of the members in all hierarchical levels are takers, for instance 99% in level 1, 85% in level 2, or 99% in level 3. There are similar patterns within the lower hierarchy (i.e. levels 1 and 2) and the middle hierarchy (i.e. levels 3 and 4): whereas there are nearly only takers in the lower sublevel within the hierarchies (i.e. levels 1 and 3), there is an increase in givers and matchers in the next higher sublevels (i.e. levels 2 and 4). Whereas levels 1 and 3 can be compared to newly qualified members or candidates, levels 2 and 4 signify members who have already been within the lower or middle hierarchy for a certain time. In the higher hierarchy, the share of matchers also increases from 9% to 17% between level 5 and level 6, while the share of givers in contrast decreases from 2% to 0%, respectively. In sum, the share of takers decreases steadily after the lower hierarchical level, starting with 99% in level 3 and ending in 83% in level 6.

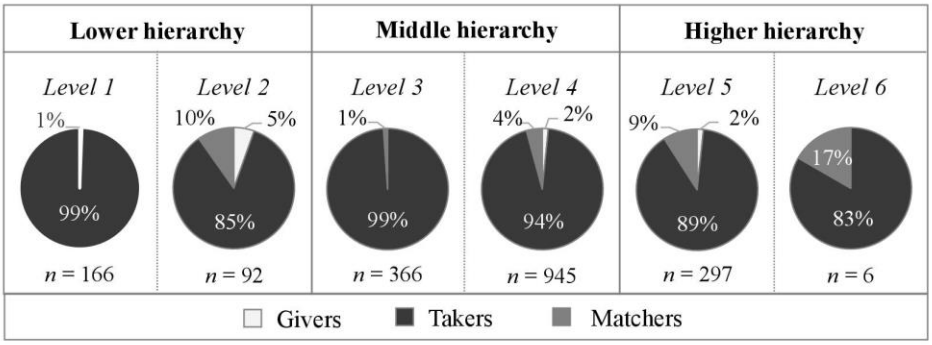

Figure 3. Allocations of givers, takers, and matchers within hierarchical levels.

5 Discussion, Limitations, and Future Research

5.1 Implications for theory and practice

In this study, we investigated knowledge exchanging behaviour in ESN as well as the structural characteristics of knowledge sharing and seeking users. In doing so, we used data about read and write accesses in the knowledge base of MSU-Net as indicator for sharing and seeking knowledge.

First of all, we proposed two novel methods to distinguish between givers, takers, and matchers in ESN. To do so, we developed the "Absolute Distance Measure" and the "Relative Distance Measure". We could show that both methods lead to very similar results. Indeed, we observed no statistically significant change in the assignment of users to the categories. Since the "Relative Distance Measure" is more complex to apply, one may tend to apply the "Absolute Distance Measure" when classifying users based on their role in the ESN's knowledge sharing activities. On this methodological basis, we found that the clear majority of all users of the ESN behave as takers. This is in keeping with Nielsen (2006) who states that only 10% of all users of a social community create 100% of its content and Katz (1998) who identified 90% of online community members as lurkers. In addition, Trier and Richter (2015) state that a smaller group of information contributors in organisational network domains competes for a large group of retrievers in order to grow their topic. The large number of takers in the knowledge base might be due to an uncertainty of the users if their knowledge is important enough to be published. Also a lack in experience in how to correctly author articles which are accessible by all other users can be a barrier, as in the case of errors it could redound upon the author. Moreover, writing an article always involves effort which some users might not be willing to make. From a practical point of view, our results imply that the small group of "givers" needs to be identified and addressed individually as key users in order to support an effective and successful exchange of knowledge within the organisation.

Second, the classification of users as givers, takers, and matchers allows us to investigate the structural characteristics of each category. Our analysis shows that givers and matchers are characterised by a high amount of written direct messages as well as a large number of social relationships and therefore are very active users. Concerning the knowledge base, givers are by far the highest contributors by writing more than six times the amount of articles than matchers do. Surprisingly, takers have only few read accesses as well as written and received messages and social relationships and therefore are overall rather passive users. They could have been expected to be more active in order to gain knowledge from the network. Our study is the first considering two aspects for characterising the user categories: knowledge sharing and seeking behaviour in the knowledge base as well as communication activities and connectedness between users. Prior studies in other contexts like tagging (Thom-Santelli et al., 2008) or blogging (Jackson et al., 2007) focussed on only one aspect for the classification of user groups. For instance, Thom-Santelli et al. (2008) investigated merely the use of tags, or Jackson et al. (2007) only considered writing and commenting blogs of users, without taking into consideration network structures. Our study does not only support the identification of important users for the knowledge exchange within an organisation, but also helps to understand how these users are characterised in terms of their connectivity and activity in ESN. Additionally, givers and matchers are well connected with respect to different centrality measures both in the social as well as in the activity graph. As regards practitioners, this means that givers and matchers are not only important for knowledge exchange in the ESN, but they can also help for example to effectively distribute information in an ESN (due to high closeness centrality). Moreover, they can for instance contribute to bridging structural holes (Burt, 1992) between sub-networks in the ESN which do not or only little overlap (due to high betweenness centrality). Hence, givers and matchers can enable a more effective and rapid exchange of information between different working groups which are for instance only sparsely connected, or more generally speaking are crucial for the diffusion of innovative ideas which essentially depends on how people are connected and influence each other (Ciriello and Richter, 2015; Ciriello et al., 2013). For this part, our results are also in accordance with Berger et al. (2014) who showed that users adding value for others are amongst the best connected users in ESN.

Third, our results also indicate that the allocations of the user categories change within hierarchical levels. Although the majority in all levels are the takers, their percentage decreases whereas the matchers' percentage increases, the higher the position in the formal organisational hierarchy is. This holds true for all observed periods. Whereas the decrease of the takers is in accordance with Grant's findings, we cannot confirm his statement that givers are the most likely to reach the end of the success ladder for the context of ESN. This might be due to the fact that ESN are an environment in

which contents can be shared easily and thus the consumption of knowledge is facilitated which in turn leads to rather a matching than a pure giving mentality. Although the share of givers increases within the lower and middle hierarchy, which shows that having a giving mentality may benefit promotions to the next hierarchical level, this does not hold true for the higher hierarchy. A reason for the shift from a taking to a giving or matching behaviour within hierarchical levels can be that at the beginning, they are careful and uncertain about the competitive situation and thus aim at gaining knowledge themselves without caring about others, yet as they want to prove themselves in a first step. But the longer they are within a hierarchical level, the more confident they become to post relevant knowledge and the more they give to others. Therefore, they lose the fear of actively contribute to the knowledge base but still mostly expect knowledge in return (i.e. these people rather behave as matchers than as givers). For practice this means that it is the members of the higher hierarchical levels that need to be addressed in order to spread knowledge through the organisation. An exception can be recognised in level 3 where the proportion of givers and matchers decreases back compared to level 2. The reason may be that right after being promoted to the next higher hierarchy for the first time (i.e. after the lower hierarchy) the willingness to share knowledge decreases but increases again after being a member of this hierarchy for a certain time. Another prominent observation is the exceptional portion of givers in level 2 which we explain in such a way that new members in level 1 are still very uncertain whereas they gain their first self-confidence in level 2 after being member for a while and start giving even more than they expect in return. But already after being promoted to the next higher level (i.e. level 3) this giving mentality decreases back and rather turns into a matching mentality due to an increasing competitive environment in higher levels which finally even culminates in a 0% share of givers in the highest level (i.e. level 6).

5.2 Limitations and further research directions

Although our results provide first interesting insights into the classification and characteristics of givers, takers, and matchers in ESN, there are several limitations, which can serve as starting points for future research. First, we only considered one single organisation, which provided us with the relevant data needed to conduct this research. Nevertheless, the ESN was actively used by a large number of users for sharing and gaining knowledge. Thus, we assume that our findings also hold for other organisations. Second, military organisations might differ from business organisations in some points. But according to the work descriptions in the Administrative Order on the Position of the Military Superior military ranks can be seen as equivalent to formal job titles in organisations like upper, middle, and lower management. Hence, we do not think that users' behaviour in MSU-Net differs from users' behaviour in other ESN. Third, we classified users as givers, takers, and matchers based on their number of write and read accesses in the knowledge base. Obviously, the participation in the knowledge cannot completely reflect users' knowledge exchanging behaviour in the whole ESN, which also takes part in direct messages. Moreover, we did not consider the extent and quality of write accesses as well as the length of read accesses. However, it may well be assumed that the knowledge base is the main feature for knowledge sharing in the ESN. While in a first step it seemed appropriate to use users' write and read accesses for the classification, further studies are needed to analyse this aspect in-depth. Besides these limitations, we see promising starting points for future research. First, we focused on users' hierarchical level as a first indicator for the professional performance of givers, takers, and matchers. Further in-depth analysis on this topic seems to be a promising starting point for future research. Are givers the most successful employees in the organisation? Does it pay off being a giver or is it more beneficial to behave as a taker (e.g., are there differences in wages or bonuses)? Do givers really reach the next hierarchical level more easily? Second, it would also be of interest to analyse if givers, takers, or matchers in the online context change to another category in the offline context. In the course of this development it would also be of interest to incorporate further characteristics of each user category beyond the social embeddedness (e.g., demographics) in order to get a more comprehensive picture.

6 Conclusion

Ever more organisations have been adopting ESN to foster collaboration, communication, and knowledge sharing among their employees (Aral et al., 2013; von Krogh, 2012). While there is a growing body of literature on ESN in general and knowledge sharing in ESN in particular, we still observe a lack of research on employees' knowledge exchange practices in ESN, for instance how users share and seek knowledge in ESN. Thus, the aim of this paper is to investigate how users can be classified based on their knowledge exchanging behaviour and how users in each category are characterised with respect to their structural characteristics as well as their position in the organisational hierarchy. Our analysis is enabled by a plethora of data generated when users interact and connect with others (Giles, 2012). Against this background, we analyse a large scale dataset of ESN usage.

First, we show how users can be classified based on their participation in the knowledge sharing process in ESN. Here, we were able to show that most users in the ESN can be classified as takers and therefore, acquire disproportionately much knowledge compared to the amount of knowledge they contribute for others. Second, by applying SNA (Wasserman and Faust, 2009) we found that givers, who share more knowledge in the ESN than they acquire from it, are characterised by a high number of written direct messages and social relationships in the ESN. Moreover, they are also well connected both in the social and the activity graph, giving them, from a structural perspective, a central position in the ESN. Therefore, organisations are well recommended to identify and address their givers for an effective knowledge management within the organisation.

With our results, we hope to contribute to a better understanding of ESN and the online knowledge exchange within organisations in particular. Summing up, we believe that our study is a first but indispensable step with regard to studying users' knowledge exchanging behaviour in ESN. We hope that our present results will stimulate further research on that fascinating topic and support practitioners to better understand and use ESN for knowledge management.

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3.2 Paper 5: "Thanks for sharing" – Identifying Users' Roles Based on Knowledge Contribution in Enterprise Social Networks

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"Thanks for sharing"—Identifying users' roles based on knowledge contribution in Enterprise Social Networks

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ABSTRACT

While ever more companies use Enterprise Social Networks for knowledge management, there is still a lack of understanding of users' knowledge exchanging behavior. In this context, it is important to be able to identify and characterize users who contribute and communicate their knowledge in the network and help others to get their work done. In this paper, we propose a new methodological approach consisting of three steps, namely "message classification", "identification of users' roles" as well as "characterization of users' roles". We apply the approach to a dataset from a multinational consulting company, which allows us to identify three user roles based on their knowledge contribution in messages: givers, takers, and matchers. Going beyond this categorization, our data shows that whereas the majority of messages aims to share knowledge, matchers, that means people that give and take, are a central element of the network. In conclusion, the development and application of a new methodological approach allows us to contribute to a more refined understanding of users' knowledge exchanging behavior in Enterprise Social Networks which can ultimately help companies to take measures to improve their knowledge management.

1. Introduction

It is forecast that the global market for Enterprise Social Networks (ESN) will grow by a 19% average year-on-year which means the annual revenue will hit $3.5 billion by 2019 [1]. ESN are online platforms used in a business context, which facilitate lightweight communication via short messages and provide functions to find, connect, and interact with colleagues [2]. With their ability to offer large-scale benefits in enterprise communication, collaboration, knowledge sharing, and thus organizational knowledge management [3–5], they are gaining rapid adoption [6]. The intention behind is to improve communication practices as well as business agility through an enhanced employee engagement [7,8]. As a matter of fact, ESN can create competitive advantage favoring effective and efficient business [9,10].

First studies have shown that these social technologies can support knowledge practices like information seeking, knowledge sharing or expert finding [11–13]. In this context, users' rationales behind online knowledge sharing [e.g., [14,15]] and knowledge seeking [e.g., [16–18]] as well as the relationships between both aspects [14,19] have already been investigated. Moreover, prior studies have identified users' roles based on the users' knowledge contribution behavior in ESN. These studies focus mainly on the users' structural positions and characteristics in networks [e.g., [20–22]].

However, in this context there is still a missing understanding of how different users and their roles impact ESN usage and how the underlying network structures influence information dissemination and contribution behavior [18]. More specifically, to the best of our knowledge identifying users' roles based on the contents exchanged in an ESN has not yet been subject of academic discussion. This perspective bears huge potential as about 80% of an organization's information is contained within text documents [23] and there are calls to deepen the understanding of these potentials [e.g., [24,25]]. Therefore, our objective in this paper is to regard the knowledge practices of ESN users from a content perspective and identify users' roles based on their knowledge contribution in contents, in particular in messages. As a consequence, we address the following research questions:

1. How can users' roles in ESN be identified based on users' knowledge contribution in messages?

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2. How can the users be characterized depending on their roles and the messages that they exchanged with other users?

In order to answer these questions, we suggest a new methodological approach consisting of three steps namely "message classification", "identification of users' roles" and "characterization of users' roles". We apply the approach to a large volume of ESN communication data from a multinational consulting company using the ESN Yammer, to come to a better understanding of the characteristics of the messages written and the users connected on the platform. A text analysis approach allows us to classify messages as "knowledge sharing" and "knowledge seeking". On this basis, we identify users depending on their knowledge sharing and seeking behavior in messages, i.e. their knowledge contribution in the ESN. In detail, we identify givers (users who outstandingly share knowledge), takers (users who outstandingly seek knowledge), and matchers (users who share and seek knowledge to a relatively balanced extent and therefore are in-between the two extremes of givers and takers). In addition, we analyze the structural characteristics of the users via Social Network Analysis and further activities in the network as well as the characteristics of the messages written by users of each user role.

Our results indicate that the majority of messages aim at sharing knowledge as compared to seeking knowledge. Moreover, most users contribute knowledge for others but also expect information in return which identifies them as matchers. Those users are also among the best connected users which gives them a central position in the ESN.

Our contribution to theory and practice is first of all the new methodological approach to analyze users' knowledge exchanging behavior and its application to ESN data from a multinational consulting company: (1) We distinguish ESN users' messages based on their knowledge sharing and seeking content via text analysis. (2) We identify users as givers, takers, and matchers based on their knowledge contribution, which depends on their knowledge sharing and seeking messages. (3) We investigate the characteristics of the users' roles such as typical structural positions in the network and content patterns or lengths of their messages. Moreover, the application of our approach reveals results that contribute to a more refined understanding of ESN usage and can ultimately help companies to improve their knowledge management.

The remainder of this paper is structured as follows: We first review the existing literature on knowledge sharing and seeking as well as users' roles based on knowledge contribution in ESN and identify the research gap. We then describe the context of our case study as well as the analyzed data and provide insights into the used method. Afterward, we present our results, followed by a discussion. We conclude with our contribution and an outlook on future research.

2. Background and related work

In recent years, organizations discovered the potential of ESN to facilitate corporation-wide knowledge exchange without being subject to departmental or geographic boundaries [2] and contribute to more open and participative communication practices [26–28]. By now, ESN are often considered a crucial means for companies to stay competitive [3]. Research about ESN already covered the adoption of ESN in organizations [29], the development of relationships between employees [18,30], the potential benefits of ESN in the corporate realm, including expert finding, problem solving, work coordination, and opinion sharing [12,31,32] as well as ESN's influence on career paths [33] and the relationship between ESN and formal hierarchies [34,35]. Yet, there is an increasing call to better understand the behavior of users in ESN [36,37], especially in reference to information diffusion [38] and knowledge exchange [39,40].

2.1. Knowledge sharing and seeking in Enterprise Social Networks

Sharing with others and demanding in return is a natural behavior pattern of mankind. When interacting with each other, individuals have to decide between the two extremes whether to claim as much value as possible or contribute value without expecting anything in return [41]. Reciprocity has been considered as one of the most important factors that determine individuals' knowledge contribution or sharing behaviors in online communities [42,43]. The consideration of knowledge as public good allows that knowledge exchange is driven by care for the community rather than by self-interest [44]. Hence, a person who has gained something from someone else tends to give something back in return in order to sustain ongoing supportive exchanges [45]. Against this background, reciprocity becomes a dominant determinant of knowledge sharing behavior [46,47].

On a related note and following the increasing demand to better understand the users' knowledge contribution in ESN, research started to investigate knowledge sharing and seeking of ESN users. There is a significant body of research showing that enterprise social software, such as ESN, is used for knowledge exchanging rather than for socializing [e.g., [48,49]]. Hence, employees engage with the aim of searching and finding new corporate knowledge, which shows that the value for the employee is rather based on information-gathering as opposed to social purposes [50]. Jackson et al. [48] and Thom-Santelli et al. [51] find that users of corporate tagging and blogging systems aim at providing information and being thought as leaders rather than seeking information for themselves or connecting with colleagues for social purposes.

In this line of research, in particular the individuals' rationales behind online knowledge sharing [e.g., [14,15]] and seeking [e.g., [16]–[18]] as well as the relation between online sharing and seeking knowledge [14,19] are investigated. Concerning the knowledge exchanging behavior in ESN, Wasko and Faraj [17] investigate the reasons why some users contribute more than others. They find that users do so if they notice an enhancement of their professional reputation, enjoy helping others, are structurally embedded in the network, and/or if their experiences are worth sharing with others. They further identify the obligation of reciprocity, i.e. giving back to the community in return for help, as drivers of knowledge sharing behavior [52]. In this context, Nowak and Sigmund [53] and Mathews and Green [54] state that reciprocity derives from the desire to repay the help or knowledge received from the community before. The relevance of reciprocity for knowledge sharing has also been confirmed by other studies [e.g., [42,43,55]]. Kankanhalli et al. [16] find that knowledge self-efficacy and enjoyment in helping others significantly impact knowledge contribution to electronic repositories whereas the loss of knowledge power and image do not appear to have any impact. Zhang and Wang [18] state that a person's position in the network influences the decisions about his or her total contribution as well as the allocation of his or her efforts on the platform. Schroer and Hertel [15] refer to contributions in an encyclopedia and find the predictors of contributors' engagement and satisfaction to be determined by perceived benefits, identification with the community, and task characteristics. Besides, their engagement depends on their tolerance for opportunity costs and the experienced characteristics of their tasks, which again is partially mediated by intrinsic motivation.

Further studies regard knowledge sharing and seeking in ESN from the content perspective and analyze the contents shared and exchanged within ESN as sources of knowledge. Riemer and Richter [56] explore communication patterns in ESN text messages by applying manual text analysis to 648 posts and find that the texts can be classified in different genres, such as "Ask questions", "Share information", or "Discuss and clarify". They conclude that

communication in their case is targeted toward providing awareness information for others and coordinating task and team matters. Cleveland [57] states that social networks in the corporate context enable users to re-post texts of other users in their own network which makes sharing knowledge with new audiences possible. They therefore allow for capturing and transferring project knowledge in organizations and facilitate the conversations between users for the purpose of sharing lessons [58]. Zhang et al. [59] investigate an ESN at a Fortune 500 company in a 5-month study and find that the platform is mainly used to share information through messages with specially formed groups that particularly engage in long conversations, which in turn facilitates knowledge sharing among the employees. They show that users can more easily build connections, find answers to specific questions, and that the informal communication is improved. In an approach to classify text documents, Ebner et al. [60] conduct a study by tracking students' messages in an ESN which was used for communication, collaboration, and documentation during a course. Of a total of 11,214 posts which were manually assigned to pre-defined categories, 60% could be identified as reply posts, indicating a clear communication process between users. These results indicate potential for informal learning and project-oriented communication on the platform. In keeping with this, Zhao et al. [61] examine the virtual network communication of a large IT company and find that 91% of the 886 posts were work-relevant, more precisely 44% were associated with tasks statuses, 19% with information and idea sharing, 18% with other work-related statuses, and 6% with questions.

Indeed, while contents exchanged in ESN have already been analyzed in prior research, to date the content perspective has not been subject to research concerning users' knowledge sharing and seeking behavior in ESN in particular. We assume that it is essential to not only investigate the rationales behind and relationships between knowledge sharing and seeking in ESN but to likewise consider the content perspective in particular in messages when analyzing users' knowledge contribution. Thus, the users' knowledge contributions to an ESN are determined based on their knowledge sharing and seeking messages using text classification algorithms. Indeed, in this context automated approaches are needed due to the rising popularity of ESN and thus the rising amount of written messages available.

2.2. Users' roles based on knowledge contribution in Enterprise Social Networks

Social scientists state that people differ tremendously in their preferences for reciprocity—their desired mix of giving and taking. Against this backdrop, Grant [41] classifies people as givers (i.e. people who give more than they get), takers (i.e. people who get more than they give) and matchers (i.e. people who try to trade evenly). Also in terms of knowledge contribution in ESN not all users can be considered as equal [e.g., [20–22]]. They differ, for instance, regarding the contents they produce with respect to frequency, volume, and quality [62]. To analyze the users and their roles more in depth, Grant's framework can serve as a starting point as it helps to differentiate between people with preferences for sharing knowledge or seeking knowledge in ESN.

People's roles in terms of knowledge contribution have been analyzed in the context of knowledge work. Knowledge work is rooted in the transformation of the society into a post-industrial state where work shifted from being manual to non-manual. The feature differentiating knowledge work from other conventional work is that its basic task is thinking [63]. Hence, knowledge workers' primary purpose involves the creation, distribution, and application of knowledge [64]. Among the roles are central connectors, boundary spanners or peripheral specialists [e.g., [65]]. Reinhardt et al. [66] identify ten knowledge worker roles depending on their knowledge sharing and seeking actions and propose among others controller, helper, learner, linker, networker or sharer as roles.

Former research in the context of users' roles in ESN already addresses the users' structural positions in the network and finds that only a few individuals receive a majority of the attention in ESN [20]. Furthermore, there is often a small number of very active users as contrasted with a large number of rather passive users, so called lurkers [21,22,67]. Nonnecke and Preece [68] find that the share can range to as much as 99% of the users and point out that there are different reasons for lurking in online social networks, with usability problems or reluctance being examples [69]. Schneider et al. [70] draw the connection between epistemic curiosity as personality trait and emotional-motivational state to lurkers' contribution in online communities and reveal that the psychology of curiosity generally holds great promise for research on online communities in information systems.

Understanding why users share and seek knowledge is especially important with respect to ESN, as users largely differ in terms of connectivity (e.g. number of friends), communication activity (e.g. number of messages) as well as frequency, volume, and quality of the user-generated content [62]. In this regard, Gloor et al. [71] analyze users' contributions in networks based on their communication patterns. They examine the users' contribution index, i.e. the extent to which their communication is balanced between sending and receiving messages, and are able to identify leadership roles. Trier and Richter [72] identify two different and interrelated actor roles as an explanation for uneven levels of user contributions to ESN. They call them discourse drivers and information retrievers as two mutually interdependent actors, which together shape the dynamics of the online interaction. On a related note, Beck et al. [25] identify knowledge contributors and knowledge seekers as two interconnected user roles in terms of knowledge exchange by analyzing their characteristics as well as their dyadic relationship from an activity-centered language/action point of view. Holtzblatt et al. [73] differentiate between active contributors, moderate contributors, and readers as well as active and occasional users while analyzing log data. Moreover, Berger et al. [74] focus on users' structural aspects and coin the term of value adding users. They find that the users who add value to the organization by sharing their knowledge in the ESN are among the best connected users and thus enable a more effective and rapid exchange of information between different working groups. Additionally, Cetto et al. [24] investigate knowledge sharing and seeking of ESN users in a knowledge base and identify givers, takers, and matchers based on their number of write and read accesses.

With our study, we build upon these approaches. While the majority of studies concerns solely users' structural characteristics, we want to focus in particular on the contents exchanged and identify users' roles based on knowledge contribution considering the content perspective in addition to the analysis of users' structural aspects. In detail, we aim at identifying givers, takers, and matchers in ESN based on their knowledge sharing and seeking in messages. While most research on user roles in ESN focusses on solely two contrary user roles, only few researchers also define user roles being in-between these extremes. Holtzblatt et al. [73] for example shape the term of moderate contributors as user role between active contributors and readers. Reflecting the research on knowledge work, indeed roles being mixes of contrary roles were proposed. Among them are linker, networker, and helper. Linkers are described as "people who associate and mash up information from different sources to generate new information" while networkers are "people who create personal or project related connections with people involved in the same kind of work, to share information and support each other" [66, p. 11]. Helpers can be defined as "people who transfer information once they passed a problem" [66, p. 11]. Nevertheless, these roles do not entirely explain the

meaning of matchers and thus are not applicable for the purpose of our study. For this reason as well as for consistency reasons we decided to stay with the term matcher to ensure an adequate analysis.

3. Research gap

Multiple authors emphasize the benefits of social media like ESN for knowledge practices [11–13,75]. At the same time there is still a missing understanding of how different users and their roles impact ESN usage and how the underlying network structures influence information dissemination and contribution behavior [18]. Previous studies recognized that users differ in their contribution in ESN and identified users' roles according to their activities and structural characteristics in the network. Cetto et al. [24] provide a first step toward the identification of givers, takers, and matchers. However, they only focused on the users' structural characteristics and the mere number of write and read accesses in the ESN, but did not take into consideration the content perspective. As 80% of an organization's information is contained within texts [23], such as messages, it bears huge potential to also consider the contents within ESN as sources of knowledge. Furthermore, content analysis have already been conducted in comparable network contexts for the purpose of analyzing contents as sources of knowledge [e.g., [56]]. In addition, related research already called for further analyses of the contents when investigating knowledge contribution in networks [e.g., [24]]. Therefore, we assume that investigating users' roles based on knowledge contribution in contents harbors enormous potential for research about knowledge contribution in ESN.

Hence, we build upon the approach of givers, takers, and matchers based on knowledge contribution in ESN and enrich this research stream by adopting the content perspective for the identification of the users' roles. Against this background, to the best of our knowledge we are the first to identify givers, takers, and matchers based on their knowledge sharing and seeking in messages using text analysis.

4. Methodological considerations

4.1. Case context

The selected case organization is a large multinational consulting company, which employs more than 180,000 people in 40 countries worldwide. In September 2008, a small group of consultants at the Dutch division of the company started to use Yammer.com, a web-based platform launched in the same month.

Yammer is a cloud service and as of today is used by about 500,000 companies worldwide as well as of 85% of the Fortune 500.[1] The functionalities of Yammer are based on the "follower principle" where users choose whom they follow and can see by whom they are followed which can be seen on each user's profile. Another feature of Yammer is the opportunity to create groups with regard to certain topics which can be joined by users of the whole network and in which users can send messages to the group members accordingly. Further platform features include profile information, options to send direct messages, and to like and bookmark posts.

The group of consultants was interested in creating an ESN environment to support their knowledge sharing by connecting employees with each other, creating more transparency, and making information easier to find. As such use practices were not yet established in the organization, the group of facilitators wanted to explore if and how the desired working practices could be established on the platform.

[1] https://products.office.com/de-de/yammer/yammer-overview.

4.2. Dataset

The dataset arises from the first 2 years of Yammer usage in the company and was provided in MS Excel format for 10,432 unique users of the platform. 7,304 of these users followed at least one other user of the platform. To ensure confidentiality, all personal information (e.g. user names, email addresses) had been removed prior to handing over the data. The data contain 110,910 messages posted inside the ESN during the time period which were written by 9,806 users. Each message consists of metadata such as message ID, user ID, timestamp, and the content of the message. In Yammer, a message can either be sent to one person or a group as private message or as a public message which can be seen by the whole network accordingly. Excluding messages with no content, each message consists of a minimum of one and a maximum of 509 terms. 5,242 messages (4.7%) were sent to one recipient (direct communication), 35,273 messages (31.8%) were sent in groups, and 16,719 messages (15.1%) were private. Furthermore, the data comprise 14,946 likes in reply to messages that were sent by 984 users of the platform. In addition, the dataset includes 599 bookmarks which were stored by users for later retrieval and information about 282 groups which the users can become a member of.

4.3. Data analysis

Our study aims at investigating the users' knowledge contribution in ESN to identify them as givers, takers, and matchers based on their knowledge sharing and seeking messages (cf. Fig. 1). By this means, it intends to provide further insights on users' roles based on knowledge contribution in ESN. Those users are regarded as matchers who share and seek knowledge to a relatively balanced extent. Users who outstandingly share knowledge (as compared to matchers) are regarded as givers whereas users who outstandingly seek knowledge are regarded as takers.

As a vast amount of company knowledge is contained within employees' written texts [23], we base our study on the users' knowledge contribution via ESN messages. Against this backdrop, we analyze messages in the ESN in a first step. Therefore, we classify messages as professional versus non-professional as merely the exchange of professional knowledge is relevant for the company's stock of knowledge. The professional messages are subsequently classified as knowledge sharing versus knowledge seeking messages. This serves us as a basis for identifying the users' roles based on their knowledge contribution in a second step. We identify each user as giver, taker, or matcher based on his or her previously identified knowledge sharing and knowledge seeking messages. To get deeper insights, we furthermore investigate in a third step the characteristics of the users' roles—such as typical structural positions in the network and content patterns—and finally triangulate the results with user interviews. Fig. 1 provides an overview of our mixed methods research approach [110]. It is composed of three steps which are discussed more in detail in the subsequent paragraphs.

4.3.1. First step: message classification

In order to substantiate the definitions of givers, takers, and matchers for our setting, we first conduct text analysis to the messages written in the ESN. The aim is to find first, professional messages as a basis for further analyzing these professional messages in terms of their knowledge contributing content. For our study, only the professional messages are of interest as source of company relevant knowledge for further content analysis. As a common proceeding to identify relevant content in mass text-based

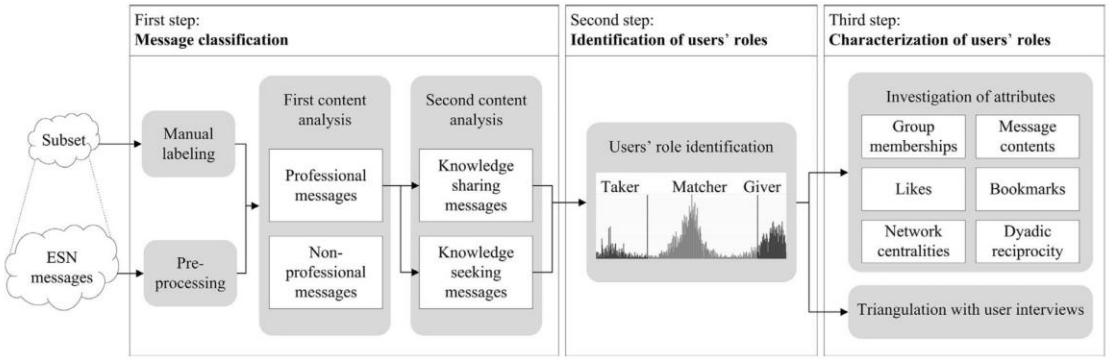

Fig. 1. Research approach.

messages, text analysis, consisting of the substeps *data preparation, data preprocessing, classification*, and *classifier evaluation,* is widely used as it has been proven to deliver reliable results [e.g., [76–78]].

In text analysis, sample labeling is a critical step in order to train a classifier [e.g., [79,80]]. Therefore, during the *data preparation* substep of our content analysis, we first construct a profile for each class. We define "professional" messages as containing information about the work in the company (e.g., technologies, directions, responsibilities, staffing) and/or about the network (Yammer) itself (e.g., functionalities). "Non-professional" message contents are regarded as non-informing or not work-related. Following this, we further subdivide the professional messages into the classes "knowledge sharing" and "knowledge seeking". In line with this, a message is regarded as "knowledge sharing" if it contains helpful information for other users (e.g., advices, helpful links, email addresses, references to documents or responsible persons), or if it offers help to other users. A "knowledge seeking" message in turn contains signs that the user receives information, demands for information, or demands help from other users. Hence, a team of two researchers manually code a randomly selected subset (training and test data) of 5% of the 110,910 messages to the corresponding class depending on the prevalence of the clear operational definitions above [81]. Therefore, each selected message is first coded to one of the two categories "professional" and "non-professional" . Afterward, if and only if the message is labeled "professional" it is further coded in "knowledge sharing" or "knowledge seeking". Regarding the coding procedure, to ensure reliable results, the researchers first define coding rules and label a first amount of messages together. After coding further 100 messages separately, Krippendorff alpha [82] as standard reliability measure for coding data [83] was used to estimate the inter-rater reliability and to ensure a consistent coding approach and reliable results. The two researchers reached a relatively high inter-coder reliability of $\alpha = 0.8802$. After consolidating the mismatches and refining the coding rules, each researcher codes by himself in order to reach a maximal subset of coded messages. We use 80% of this labeled data (training data) to train a classifier, utilize the remaining labeled data (test data) for classifier evaluation, and subsequently apply the classifier to the whole dataset.

In the following substep, *preprocessing* is used to clean the data and reduce the amount of terms to get the minimum of relevant terms to improve speed and accuracy of classification algorithms [84]. Preprocessing is composed of *feature extraction, feature representation*, and *feature selection. Feature extraction* is used to extract relevant features from the original text documents in a clear format [85]. Therefore, we remove all messages not relevant for our purpose, which are automatically generated messages (e.g. welcome notes and daily reports) identified by their standard structure and non-English messages identified by the Apache TIKA library.[2] Moreover, we conduct term manipulations to the texts in order to reduce the count of terms in such that we remove hyphen, markups from html, punctuations (except for question marks which are replaced by "questionmark" as they are assumed to be relevant for the identification of knowledge seeking messages), diacritic marks and numbers. Moreover, we write all terms to lower case. We also replace terms consisting of hyperlinks, emails, tags, user names or groups by categorical identifiers (e.g. "ishyperlink", "istag") as they have the same semantic meanings for our analysis. Additionally, we remove stop words (such as "and" and "the") using the built-in list of English stop words in KNIME[3] and reduce the terms to their word stem using the common Porter Stemmer [86]. The purpose of *feature selection* is to eliminate irrelevant and redundant information from the target texts using a score mostly based on the frequency of terms [87]. We decide to eliminate features with only a single occurrence as they are not relevant for the classification. To conduct the previously described substeps we apply the commonly used bag-of-word *feature representation* for the preprocessing steps [88]. The result of the *feature selection* is represented in a vector space model in which each dimension represents a separate term as a single word with each term occurring at least once in a certain minimum number of documents [89].

In the *classification* substep, we apply text classification algorithms to the document-term matrix to assign a document to the corresponding class. In the last substep *classifier evaluation*, we aim at finding the best classification results. To do so, we test the most common classification algorithms, such as decision tree classification [90], support vector machine (SVM) [91], k-nearest neighbor (KNN) [92], naïve-Bayesian [93] and artificial neural network (ANN) [94]. We train each algorithm with the labeled training data and evaluate the classifiers based on the labeled test data. For the evaluation, we compute recall, precision, accuracy, and F1 score which are widely used to assess the results of text analysis [95] and other machine learning approaches [96]. We utilize a 10-fold cross-validation [97] and regard the performance measures accuracy and F1-score as they include the measures recall and precision. We choose SVM as algorithm as it delivers good results and performs best for the classification in "professional" and "non-professional". Moreover, it also delivers good results for the classification in "knowledge sharing" and "knowledge seeking" (cf. Table 1).

[2] https://tika.apache.org/1.14/detection.html.

[3] https://www.knime.org/files/nodedetails/_labs_textprocessing_preprocessing_Stop_word_Filter.html.

Table 1
Classification results (maximum values are marked bold).

	First content analysis				Second content analysis			
	Recall (%)	Precision (%)	Accuracy (%)	F1 (%)	Recall (%)	Precision (%)	Accuracy (%)	F1 (%)
ANN	81.4	**89.4**	80.6	85.2	95.6	85.4	87.0	90.2
Decision Tree	85.5	85.7	80.2	85.6	89.0	89.3	86.4	89.1
KNN	67.9	85.3	69.9	75.6	53.1	**91.8**	67.8	67.3
Naïve Bayes	**95.7**	80.1	79.7	87.2	**99.1**	70.2	73.2	82.2
SVM	90.0	88.5	**85.1**	**89.2**	92.1	89.1	**88.0**	**90.6**

4.3.2. Second step: identification of users' roles

To identify givers, takers, and matchers based on knowledge contribution in ESN we not only binarily differentiate the messages m_i^u of a user u into messages with preliminary knowledge sharing content $c_\uparrow(m_i^u)$ and preliminary knowledge seeking content $c_\downarrow(m_i^u)$ but rather we use the probabilistic outputs $P(c_\uparrow(m_i^u))$, $P(c_\downarrow(m_i^u))$, delivered by the SVM classifier [98]. $P(c_\uparrow(m_i^u))$ represents the probability that the message is knowledge sharing while $P(c_\downarrow(m_i^u))$ depicts the probability that the message is knowledge seeking. In order to establish the link between the average probabilities of users' messages being knowledge sharing and seeking, we take the differences between the averages (based on each user's amount of messages n^u) of $P(c_\uparrow(m_i^u))$ and $P(c_\downarrow(m_i^u))$. This difference represents each user's knowledge contribution to the ESN ($d_{c_{\uparrow\downarrow}}(u)$). The results of the following formula are values in the interval $[-1;1]$.

$$d_{c_{\uparrow\downarrow}}(u) = \overbrace{\left(\frac{1}{n^u}\sum_{i=1}^{n^u} P\left(c_\uparrow\left(m_i^u\right)\right)\right)}^{\text{probability of messages being knowledge sharing}} - \underbrace{\left(\frac{1}{n^u}\sum_{i=1}^{n^u} P\left(c_\downarrow\left(m_i^u\right)\right)\right)}_{\text{probability of messages being knowledge seeking}} = \frac{1}{n^u}\left(\sum_{i=1}^{n^u}\left(P\left(c_\uparrow\left(m_i^u\right)\right) - P\left(c_\downarrow\left(m_i^u\right)\right)\right)\right)$$

Based on the definition of $d_{c_{\uparrow\downarrow}}(u)$, users with $d_{c_{\uparrow\downarrow}}(u) = 1$ and $d_{c_{\uparrow\downarrow}}(u)$ close to 1 are regarded a givers, while users with $d_{c_{\uparrow\downarrow}}(u) = -1$ and $d_{c_{\uparrow\downarrow}}(u)$ close to -1 are regarded as takers. Matchers are located between givers and takers with a relatively balanced knowledge contribution. We define matchers as users whose knowledge contribution $d_{c_{\uparrow\downarrow}}(u)$ differs less than one standard deviation ($\sigma_{d_{c_{\uparrow\downarrow}}(u)}$) from the average knowledge contribution ($\bar{x}_{d_{c_{\uparrow\downarrow}}(u)}$) of all users. This results in a corresponding interval of $(\bar{x}_{d_{c_{\uparrow\downarrow}}(u)} - \sigma_{d_{c_{\uparrow\downarrow}}(u)},\ \bar{x}_{d_{c_{\uparrow\downarrow}}(u)} + \sigma_{d_{c_{\uparrow\downarrow}}(u)})$ for the knowledge contribution $d_{c_{\uparrow\downarrow}}(u)$ of a matcher. All users with a knowledge contribution $d_{c_{\uparrow\downarrow}}(u)$ outside this interval are classified as givers or takers respectively (cf. Fig. 2).

4.3.3. Third step: characterization of users' roles

To investigate the structural characteristics of givers, takers, and matchers and to analyze their social networking behavior in ESN, we apply Social Network Analysis [99,117]. In the context of ESN, Social Network Analysis was prior used to analyze for instance users' social networking behavior in ESN [35,100], or the characteristics of key users in ESN [74]. According to Freeman [101], Social Network Analysis "involves theorizing, model building, and empirical research focused on uncovering the patterning of links among actors" by, for instance, quantifying the centrality of nodes within a network via centrality measures. The most common centrality measures are degree centrality, closeness centrality, and betweenness centrality [102] as well as eigenvector centrality [103]. An ESN can be represented as a graph with a set of nodes (users) and a set of edges (ties) linking pairs of nodes. The edges can be directed or undirected and represent either social links like follower relations (social graph) or communication activities like messages among the users (activity graph) [104–106]. We base our research on both graphs in order to get profound insights into the structural characteristics of givers, takers, and matchers in ESN.

We analyze two different types of relationships: (1) social relationships (based on directed follower relations) and (2) communication (based on direct messages). In the case of *directed follower relations*, the social graph contains 9,237 nodes (users involved in at least one follower relationship) and 137,550 directed edges created by users who follow. Concerning *communication*, nodes represent senders and recipients of messages, while edges are created by sending a message. The corresponding activity graph contains 1,327 nodes (users being senders and/or receivers of at least one direct message in the observation period) and 2,660 directed edges. For our analysis, we use the igraph package for *R*[4] to calculate degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality for each node of the social as well as of the activity graph. In addition, we investigate a further network measure related to the users' reciprocal behavior. This measure refers to the behavior of responding to an action in the network with another action [107,108]. In ESN, reciprocal behavior shows up as retweeting, commenting, liking or answering one another's post or message to ensure ongoing mutual support. This reciprocity is regarded as dyadic level of analysis in terms of directed reciprocity [109]. We measure the users' dyadic level of knowledge contribution in ESN based on the users' sharing messages (to individuals as well as within groups), i.e. the percentage of answering with a sharing message to a previously received sharing message.

To gain further insights into the characteristics of givers, takers, and matchers, we additionally analyze user statistics. In particular, we investigate the content patterns and lengths of their messages exchanged and the participation of givers, takers, and matchers with respect to group memberships, usage of tags, bookmarks, and likes as well as messages received and sent (overall, private, public).

Finally, according to Behrendt et al. [110] combining results from different sources can improve the validity of the analysis. Thus, to draw a richer picture of the case context and complement our quantitative results, we decided to triangulate them with interviews with 14 users of the ESN which had been carried out earlier in order to get a better understanding of the ways users have appropriated the platform [111]. Yet, quotes from the interviews also proved helpful to illustrate how the ESN users reflected upon their behavior as well as on the behavior of others.

[4] http://cran.r-project.org/web/packages/igraph/index.html.

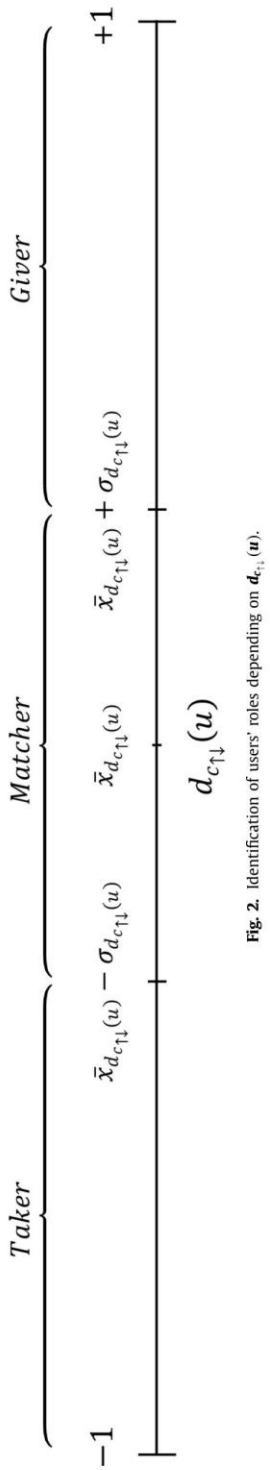

Fig. 2. Identification of users' roles depending on $d_{c\uparrow\downarrow}(u)$.

5. Results

This section is dedicated to the results. First, we focus on the results of the message classification. The second part concentrates on the results of the identification of users' roles and the third part reveals the characteristics of the users' roles in terms of structural positions in the network and content patterns as well as the triangulation with user interviews.

5.1. Results of the first step: message classification

The results of the first step "message classification" reveal that professional messages are prevalent with a share of 72.4% in the ESN and exceed non-professional messages (27.6%) in many ways: they exhibit in total a vaster amount of messages, have a higher term variety as well as more terms per message as opposed to non-professional messages (cf. Table 2). Further, the majority of professional messages is classified as knowledge sharing with a share of 64.9% as opposed to knowledge seeking (33.1%). As to that, the knowledge sharing messages show higher amounts regarding term variety as well as terms per message indicating that knowledge sharing messages in average are longer and seem to contain more information than knowledge seeking messages (cf. Table 2).

Concerning the contents of the messages (cf. Fig. 3), knowledge sharing messages include most of all the term "ishyperlink" (10,656 occurrences: e.g., "here you can read how you can do it ishyperlink") followed by "tag" (3,938 occurrences: e.g., "expecting quick market uptake of open group it specialist certification forthcoming year ishyperlink [istag] [istag]") and "n[o]t" (3,241 occurrences: e.g., "it is not a question of security but privacy"). Concerning knowledge seeking messages, the prevalent term is "questionmark" (14,836 occurrences: e.g., "any news on your potential project questionmark"), before "thank" (3,836 occurrences: e.g., "a really good ebook thanks for sharing"), and "looking[for]" (2,561 occurrences: e.g., "looking for reverences where we have done website rationalization"). The most frequent terms in knowledge sharing and seeking messages can be seen in the word clouds of Fig. 3. At this point, it should be noticed that the same term can appear in knowledge sharing as well as knowledge seeking messages (i.e., "does this help someone questionmark" or "can someone help me questionmark").

5.2. Results of the second step: identification of users' roles

As givers, takers, and matchers are identified based on their knowledge contribution in messages $d_{c_{\uparrow\downarrow}}(u)$, in the step "identification of users' roles" only users with knowledge sharing or knowledge seeking messages are regarded, which results in 2,734 users with at least one knowledge sharing or seeking message. The result of the identification of users' roles is depicted in Fig. 4 which shows the distribution of $d_{c_{\uparrow\downarrow}}(u)$ among all users as well as the separation of givers, takers, and matchers according to the thresholds.

With $\bar{x}_{d_{c_{\uparrow\downarrow}}(u)} = 0.1940$ and $\sigma_{d_{c_{\uparrow\downarrow}}(u)} = 0.5620$ the upper threshold of a matcher yields 0.7560 while the lower threshold results in −0.3681. The results reveal that most users in the ESN are classified as matchers (57.3%) as opposed to givers (28.5%) and takers (14.2%).

5.3. Results of the third step: characterization of users' roles

To get deeper insights into the structural characteristics of givers, takers, and matchers we regard indegree centrality (C_i), outdegree centrality (C_o), closeness centrality (C_c), betweenness centrality (C_b), and eigenvector centrality (C_e) for each node of the

Table 2
Message distribution and attributes.

	First content analysis		Second content analysis	
	Professional	Non-professional	Knowledge sharing	Knowledge seeking
Messages	57,056 (72.4%)	21,798 (27.6%)	38,194 (64.9%)	18,862 (33.1%)
Term variety	46,696	20,554	37,956	19,704
Terms/message	12.3	6.9	13.3	10.4

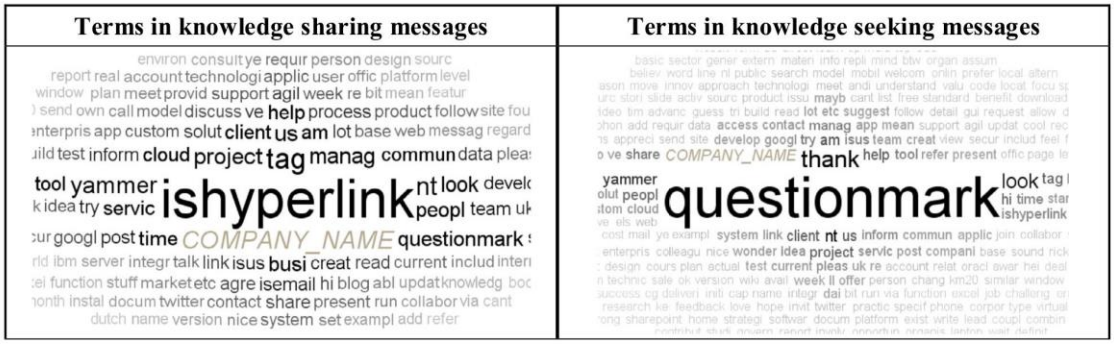

Fig. 3. Word clouds and most frequent terms.

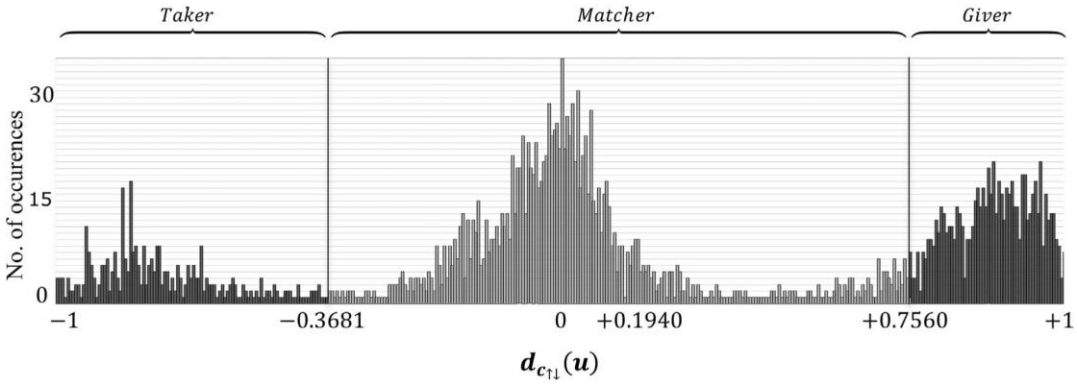

Fig. 4. Distribution of users depending on their knowledge contribution $d_{c_{\uparrow\downarrow}}(u)$.

Table 3
Average values for the network measures depending on users' roles (in %).

	Social graph					Activity graph					
	C_i	C_o	C_c	C_b	C_e	C_i	C_o	C_c	C_b	C_e	R_S
Giver	0.17	0.12	3.50	0.01	2.18	0.07	0.07	0.16	0.01	0.59	25.80
Taker	0.15	0.10	3.50	0.01	2.01	0.08	0.08	0.19	0.01	0.72	5.25
Matcher	**0.45**	**0.70**	**3.52**	**0.08**	**4.10**	**0.22**	**0.21**	**0.21**	**0.13**	**4.09**	**48.90**

social as well as the activity graph. We furthermore investigate the sharing reciprocity (R_S) for each node of the activity graph. We find matchers to be the users with the highest centrality measures as well as the highest R_S. Table 3 shows the average values resulting for givers, takers, and matchers. Similar results can be observed for median values.

We find that, regarding the social graph, matchers are among the best connected users in the network showing the highest average values for all centrality measures. This means that matchers follow in average most other users (C_o) and are most often followed by others (C_i), are the closest to all other users (C_c), are most often included in the shortest paths between two other users (C_b), and have connections to other users that are themselves very well connected (C_e). As compared to this, takers are on average the least connected in the social graph concerning all centralities, closely followed by givers who manifest a slightly better connectedness than takers. Focusing on direct communication as represented by the activity graph, the results show that again, on average, the matchers are most connected while givers and takers fall behind. This holds for all centrality measures. The result for C_c indicates that these users are generally close to all other users in the activity graph and that their messages may therefore reach a large number of users in a relatively short time. At the same time, these users are most often included in the shortest paths between two other users in the activity graph of the ESN (cf. C_b) and hence are able to control or even listen to the information exchange be-

Table 4
Average values for user attributes depending on users' roles.

	Tags	Group memberships	Bookmarks	Likes	Sent messages	Received messages
Giver	0.05	2.12	0.03	0.26	5.82	0.24
Taker	0.02	2.07	0.02	0.25	4.64	0.39
Matcher	**0.18**	**4.80**	**0.33**	**1.60**	**60.01**	**2.78**

tween other users. Givers are, on average, the least connected users concerning the activity graph, with takers being only slightly more connected than givers. Regarding the exchange of sharing messages, givers and takers do not show high levels of reciprocity (cf. R_S), but matchers do. This again emphasizes the crucial role of matchers for spreading knowledge in the network and advancing the community as a whole.

Table 4 depicts the average attributes of the different user roles. We substantiate the findings by the Social Network Analysis as we detect that a matcher writes on average 11.5 times as many messages as a giver or taker — independent of the message type (private, public, professional, unprofessional, knowledge sharing, knowledge seeking). Moreover, a matcher receives on average 7.2 times more messages as compared to a giver and 11.8 times more messages as compared to a taker respectively. Regarding the average terms per message, we detect that givers' messages contain the most (12.8 terms per message) in comparison to matchers' (10.9) and takers' (9.8). When investigating the contents of the messages exchanged more in depth, we find that givers very often share their knowledge in the form of links which inform about news in the information technology context and pass on email addresses of colleagues. They further talk about the company itself and work relevant topics (i.e. the messages broadly contain the terms "client", "projects", "management" and "team") and share presentations and internal information material as well as their experience within project work (e.g., with SAP systems). Takers predominantly search for information about the company, projects or the experience made within projects and further look for experts for project acquisition (i.e. the messages often contain the terms "look", "project", and "experience"). Matchers mainly share and demand for company and project relevant information. Yet, they also noticeably talk about the ESN itself and discuss its functionality.

In addition, when referring to other activities in the network, like the average amount of group memberships, usage of tags, bookmarks, and likes (cf. Table 4) we find that, on average, a matcher elucidates the highest participation in each aspect.

Summed up, the results of our analysis reveal that matchers take on particular importance in ESN as they are the most connected and central users concerning all centrality measures in the social graph as well as the activity graph. Moreover, they are also the most active users regarding all other activities analyzed.

Finally, the interviews with 14 users of the ESN help us to illustrate how the users reflect upon their knowledge exchanging behavior and the knowledge exchanging behavior of others. In the interviews, we found that some employees have a clear understanding of their role. For instance, one user describes himself as a taker: "I'm not an expert so I don't contribute. But I think I also do a lot of learning. I ask a lot of questions to clarify my own knowledge of certain topics. So I think my postings on Yammer are essentially to know more and its more questions than anything else." (Interview C14). Another user states that he uses Yammer to share knowledge: "[I use it] to show others how we solved problems. It's a great tool to showcase what worked and also to get feedback about what could be done better. Just the other day, I posted something and got a couple of answers – some of them pointing me in new directions, so it gave me a business benefit" (C08). This statement underlines that reciprocity enhances the motivation to participate in an ESN and therefore is a crucial aspect for its acceptance.

At the same time, a number of employees confirm that others often do not "only ask for input" (takers) or "only share knowledge" (givers) but engage in discussions where they take both sides and thus could be termed matchers. "In general it's about knowledge. Sharing knowledge and gaining knowledge. Often people use it in both ways. That's what is so great about this tool. It's easy to gain and it's easy to share." (C02). Another employee mentions the importance of matchers when it comes to appropriating the platform: "But that's the difference of users within every network. There are some more active and some less active. As long as we have enough active people, who consume but also share, the community will be sustainable" (C06). Another interviewee states: "I encourage my team as well to be on Yammer as much as possible to ensure that we don't lose that knowledge that's created out of these discussions." (C14).

Overall, the interviews most widely underpin the results of our quantitative analyses and they also show the role of Yammer as knowledge management tool.

6. Discussion

While prior studies mainly focus on structural characteristics (e.g., number of likes) when identifying users' roles based on their knowledge contribution in ESN, they do not consider the content perspective in sufficient detail [24,25,72,73]. Against this background, we propose and apply an approach consisting of three steps that allows us to distinguish between givers, takers, and matchers based on their knowledge contribution via ESN messages. Our results illustrate that the contents necessarily need to be considered in order to get reliable results as the mere consideration of the structural characteristics may lead to misinterpretations of the results (cf. also Section 6.1).

6.1. Matchers as central element of an ESN

Our results show that the clear majority of the users in the ESN act as matchers, i.e. they are willing to help others but as part of a "this for that"-approach also want to get something back. This is underscored by interviews in which users of the considered ESN shared their observations that people use Yammer to gain and to share, as it is easy to do both. Beyond that, we find that matchers play a central role in ESN as they keep the network alive due to their high network interconnectedness and activity. They are by far the best connected in the social as well as the activity graph and are also the most active concerning all other activities analyzed (such as giving likes, bookmarks etc.). These results elucidate that matchers are the most important users in the ESN as they connect the users and spread the information in the network. The fact that they receive most messages means that by demanding information from users (in turn for sharing information), they encourage other users to also participate in the ESN, and thus they keep the network alive and together. They can for instance contribute to bridging structural holes [112] between sub-networks in the ESN which do not or only little overlap (due to their high C_b) and moreover, they may enable a more effective and rapid information exchange between different working groups that are for in-

stance only sparsely connected. More generally speaking, matchers are crucial for the diffusion of innovative ideas which essentially depends on how people are connected and influence each other [113].

Referring to reciprocity, matchers are also those users who mostly give knowledge back to the community in return for help, which illustrates that they aim at bringing forward the community as a whole. This is in line with Wasko and Faraj [52] who found that giving back to a community in return for help is by far the most cited reason why people participate. It also complies with Kollock [114], who states that people helping others indeed hope to receive something back in return. He argues that these people expect interaction to be available in the future and therefore, the possibility of future reciprocation must be given. It can be concluded that companies should use technologies that show the identities of the users and archive discussions in a searchable format.

In addition to sending most messages, matchers also write in average the longest messages which indicates that they put a lot of effort in the ESN. For this part, our findings are in line with Berger et al. [74] who show that users adding value for others are among the best connected users in ESN. In addition, referring to the contents exchanged, matchers discuss more about the network itself as well as its functionalities, as compared to givers and takers who rather exchange work related information. This fosters that matchers are the central element of the ESN keeping the network alive and developing it further. Moreover, our results reveal that 50% of the messages are written by approximately 1% of the users, whereby all of these are matchers. This complies with Nielsen [115] who find that only 10% of all users in a social community create 100% of its content as well as Trier and Richter [72] who state that a smaller group of information contributors in organizational networks competes for a large group of retrievers in order to grow their topic. Moreover, also Yardi et al. [20] come to know that only a few individuals receive the majority of the attention in ESN. In contrast to other studies, our results elucidate that an investigation of the contents is crucial to reach valid results. Contrary to Cetto et al. [24] who base their identification of users' roles on the relation of read and write accesses (without considering the contents), we illustrate that solely regarding the number of messages is not sufficient. When identifying matchers based on their contents exchanged, we find that they also write most of the messages. Regarding merely the number of messages exchanged, these users would subsequently be identified as givers. Hence, understanding the contents exchanged more in depth is crucial for a reasonable identification of users' roles.

6.2. Givers and takers as less participating users

Surprisingly, givers and takers are by comparison less participating users. They write and receive rather few messages and are not as well connected in the social and activity graph as compared to matchers. Both, givers and takers could have been anticipated to be more active and better connected. Givers could have been expected to be more active through a higher absolute amount of outgoing messages and a better connectivity while takers could have been expected to gain more knowledge from the network through a higher absolute amount of incoming messages and a better connectivity respectively. A reason for the rather low connectivity of givers concerning the activity graph can be that the activity graph concerns private communication while givers might prefer to share their knowledge not in a private but rather in a public context with the aim to reach as many users as possible. But as opposed to this, givers also have comparably few group memberships. This is rather surprising as groups could be used to reach multiple users with only a single message and thus offer a good opportunity to spread knowledge more easily. Consequently, as matchers communicate most in both—the private as well as the public context—companies are well advised to precisely identify and address their matchers in order to support an effective and successful exchange of knowledge within the organization.

Nevertheless, it cannot be neglected that also givers and takers are of certain importance for the company in such that givers also have the potential to spread knowledge by giving their knowledge to others while takers are important in the sense that they can gain new work relevant knowledge through asking questions and participating in the ESN. This is in line with Beck et al. [25] who provide evidence that the mix of questions and answers in communications impacts the quality of knowledge exchanged. Hence, also these users should be encouraged to take an active part in the ESN, for instance through incentives such as a bonus for a certain participation rate in the ESN.

Our results furthermore reveal that a high amount of users is enrolled but has not even one written nor received message in the ESN at all. These so called "lurkers" make up to 63.2% of all enrolled users in our dataset. This is in keeping with Katz [116] who states that the majority (up to even 90%) of online community members can be identified as lurkers. Nonnecke and Preece [68] analyze the reasons for lurking in online communities and reveal that among the main reasons for this behavior are privacy and safety concerns, reluctance, and usability problems [69]. This is in line with the results delivered in our word clouds which show that users are still unsure how to properly use the platform and are not completely convinced of it. This leads to the assumption that these aspects can really be a problem for some users which prevent them from participating in the ESN and which in turn results in lurking.

6.3. Characteristics across all users' roles

Across all users' roles, we find that employees use the ESN primarily for professional purposes. Moreover, the majority of the professional messages are knowledge sharing which shows that the users are generally cooperative and willing to share their professional knowledge with and thus help other users. Hence, they use the network as communication channel which enables them to spread their knowledge more easily with a vast amount of people (as compared to offline communication). This is in line with Kane [5] and Aral et al. [3] who argue that social media in the organizational context support and fundamentally change the way people communicate, collaborate, consume, and create.

Moreover, the fact that the majority of messages are intended to share knowledge can lead to the assumption that only one knowledge sharing message as answer to a knowledge seeking message may not be sufficient for the explanation of certain circumstances. Users often need more than one message to explain or discuss certain aspects in depth, which in turn leads to a higher amount of knowledge sharing messages. This enriches the network as discussions can generate new knowledge and encourage other users to give their opinion and thus also share their knowledge within the network.

Moreover, regarding the message contents, our results reveal that knowledge sharing messages tend to point to helpful links and tags which in turn ensures that users find information more easily. Further, apart from work related information, knowledge sharing messages comprise information about the network (Yammer) making clear that the functionalities of the network itself are in focus of communication and need further clarification.

Our results also show that knowledge seeking messages often thank users for messages, which can indicate that the message was an answer to a knowledge sharing message following a previous question. A reason for the prevalence of sharing messages can

be that the employees of the consulting company see the ESN as a chance to stand out from the crowd and promote themselves. Through answering questions and sharing links they can show that they own a lot of knowledge and are experts in their fields. Against this backdrop, they increase their visibility in the company and might be recruited for more projects which in turn enhances their reputation and can speed-up their career path in the company. This illustrates that ESN enable companies to better detect and trace their experts which then again leads to a more efficient project staffing. This is in accordance with Berger et al. [74], who state that companies are well advised to identify their key users in ESN to enable a more effective and rapid exchange of information between different working groups. Therefore, ESN providers should better invest in the provision of analytic functions to improve the visibility of the most important users in the network.

6.4. Limitations and future research

Even though our research provides first interesting insights into the identification of as well as the characteristics of givers, takers, and matchers in ESN, there are several limitations which can serve as starting points for future research.

First, we only considered one single company, which provided us with the relevant user and message data needed to conduct this research. Nevertheless, the ESN was actively used by a large number of users for sharing and seeking knowledge and we assume that our findings also hold for other companies using ESN.

Second, for message classification, we defined knowledge sharing messages as those messages which contain helpful information or offer help to other users and we defined knowledge seeking messages as those messages containing signs that the user receives information, demands for information, or demands help from other users. Obviously, this definition cannot hold in all cases as messages can contain parts from both definitions. However, the classification algorithm used provides probabilities that a message pertains to the knowledge sharing or knowledge seeking class and thus provides the information that a message contains comparably more knowledge seeking or more knowledge sharing content. Hence, it may be well assumed these probabilities are appropriate for being used in our context.

Third, we classified users as givers, takers, and matchers based on the content of their messages. In so doing, we focused on relevant words in messages and accepted a loss of semantics as we selected and filtered words, ignored verbosity (part of speech), and the context of a message in the message flow. However, we assume that the remaining relevant words represent the main features for knowledge contribution in ESN. Further in-depth analysis regarding the context of the related thread or group in which a message is written is needed to include the message flows in the proposed approach and answer the question whether a knowledge seeking message is often followed by a knowledge sharing message. Furthermore, it would be of interest to analyze chronological orders of messages, for instance whether a discussion is started and finished by a knowledge seeking message while in between the discussion is dominated by knowledge sharing messages.

Moreover, we did not consider the time factor of the messages and the users' roles. While in a first step, it seemed appropriate to take such a static perspective, further studies are needed to analyze this aspect in-depth. It would be promising to analyze the time-based change of users' roles (e.g., from takers to matchers to givers) and the users' life cycles. In the course of this development it would also be interesting to incorporate further characteristics of the users of each role beyond the social embeddedness (e.g. demographics, position in the organization and hierarchies) in order to get a comprehensive picture of givers, takers, and matchers.

7. Conclusion

Despite emerging scientific work in the field of ESN, we still observe a lack of research on employees' knowledge exchange practices in ESN, for instance how users contribute knowledge in ESN. While there is a growing body of literature on identifying users' roles which mainly considers the users' structural characteristics [24,25,72–74], the content perspective for getting further insights in the knowledge contribution of users as well as their user roles respectively, is still widely unexplored.

Thus, the aim of this paper is to investigate how users' roles in ESN can be identified based on users' knowledge contribution in messages. Further, we determine how users can be characterized based on their roles and the messages that they exchanged with others. We propose an approach consisting of three steps that allows us to distinguish between givers, takers, and matchers based on their knowledge contribution via ESN messages.

The application of our approach to a dataset of a large multinational consulting company delivers exciting results which elucidate the importance for companies to also consider ESN as sources of company relevant knowledge. First we find that users wrote mainly professional messages and aimed at sharing their knowledge which shows that the users are generally cooperative and willing to help others. In addition to that, our results reveal that most users in the ESN can be identified as matchers and therefore, they offer and deliver information to others, but also demand information in return. Moreover, they are among the best connected, most active users in the network, giving them a central position in the ESN as they keep the network together and alive. Therefore, organizations are well recommended to identify and address their matchers for an effective knowledge management within the organization.

From a theoretical perspective, our findings contribute to the development of a more refined understanding of ESN usage in knowledge-intensive work. Through identifying users' roles we shed light on their networking behavior and help to better understand their characteristics. As such our study builds upon research on users' roles in knowledge contribution in ESN and extends its line of thoughts by using a content perspective. From a practical point of view, our insights can help companies to better understand the knowledge contribution behavior of their employees in ESN. Companies are well advised to better investigate and to become acquainted with the characteristics of their ESN users to ensure an efficient knowledge management in the company. Our study can support companies to attain this aim as it offers valuable insights in the knowledge contribution behavior of their ESN users.

Summing up, we believe that our study is a first but indispensable step in terms of studying users' knowledge contribution in ESN messages. We hope that our results will stimulate further research on that fascinating topic and support practitioners to better understand and use ESN for knowledge management.

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4. Conclusion

This last chapter summarizes the major findings of the dissertation as well as its limitations, which may serve as promising starting points for future research.

4.1 Major Findings

Due to the ubiquitous presence of digitalization in nearly each and every aspect of life, people have gotten used to digital technologies. Social media and mobile devices have become indispensable concepts of people's everyday lives, that have changed the way how people communicate, collaborate, consume, and interact with friends and family as well as with companies (e.g., Kane, 2017). Pervasive connectivity, information abundance, and global supply chains are concepts taken for granted in today's society due to opportunities deriving from various kinds of technology-enabled media. The result is that people are increasingly independent and at the same time more connected than ever before. Along with this development, in particular two new technologies have become common for people, namely SST and ESN. They have turned into crucial means for companies to stay competitive as people meanwhile even expect these technologies to be offered by "up to date" companies. Given their rapid development and increased prevalence up to the present day, their proliferation is more than likely to increase – already in the near future. This is why they have increasingly gained interest on the part of research as well as of practice. Against this background, these technologies as well as their users require further investigation in order to adapt companies' IT strategies, processes, and systems as well as the management to the new digital age.

For this reason, this dissertation focusses on SST and ESN as two powerful new trends whose importance is likely to keep accelerating. SST and ESN themselves as well as their users need to be understood more in depth so that companies can use these promising technologies in the most efficient and profitable way. This dissertation therefore addresses the highly relevant subjects of SST and ESN, especially in regard of their users' behavior and knowledge exchange, and contributes to research and practice as follows:

1) *Hedonic motivations play an important role for users' behavior (Topics 1 and 2).*

In Chapters 2.1 and 2.2, this dissertation addresses the complex nature of new digital technologies – in particular of SST –, their inherited values and what these values imply for users' be-

havior. It has been shown that users' adoption of technologies is driven by positive and negative motivations (e.g., Peter and Tarpey, 1975) as well as by motivations related to the utility it brings to the user (e.g., Venkatesh and Bala, 2008). Moreover, it can be better explained when additionally integrating hedonic motivations like the perceived enjoyment (e.g., Agarwal and Karahanna, 2000; Venkatesh et al., 2012). This dissertation addresses these motivations and proposes and evaluates two novel multidimensional research models.

First, it postulates that SST are dual technologies that are both hedonic- and utilitarian-oriented – a fact that has mainly been ignored by research to date. Accordingly, in Chapter 2.1 a multidimensional research model is developed to capture an individual's utilitarian and hedonic motivations to use SST. The results show that hedonic motivations are of particular importance (cf. Paper 1). This means that the hedonic value inherited during the actual SST usage plays an important role for users' behavior. Whereas analyses about other technologies or technologies in general often solely refer to enjoyment as hedonic motivation (e.g., Curran and Meuter, 2007; Dabholkar, 1996), it is found that the hedonic value of SST is composed of various hedonic motivations. Among them, the user's inherent novelty seeking as well as the challenge of mastering the correct usage of the new technology are among the most important.

Second, also when users decide whether to switch from kiosk SST to mobile service, the fun factor plays a crucial role (cf. Paper 2). This derives from Chapter 2.2 in which another multidimensional research model is developed capturing the positive and negative motivations influencing users' switch from kiosk SST to mobile service. The results again reveal a strong positive influence of enjoyment on the switch. This elucidates that nowadays, in a fast-paced and high-performance-oriented world, people want to have a feeling of pleasure when getting things done – in various aspects of daily life. Accordingly, companies have to design new digital technologies, like SST, so that they address not only task-related motivations such as time savings, reliability, or control, but also hedonic motivations that provide "self-fulfilling value to the user" (van der Heijden, 2004, p. 696) such as enjoyment, novelty seeking, and challenges. This is all the more important if firms aim to increase the usage rate of their SST and want to address people rarely using SST so far.

2) *Motivations related to the modern lifestyle play an important role for users' behavior (Topics 1 and 2).*

The results of Chapters 2.1. and 2.2 further reveal that the motivations driving users' behavior are mostly related to their lifestyles, such as compatibility or time savings, elucidating that traditional values which can only be provided by service employees, such as being recognized, listened to, valued, and cared for, lose importance for the digital user.

First, Chapter 2.1 shows that the motivations related to reliable service delivery and time savings are among the most important for the use of SST. This does not seem surprising in today's fast-paced world where topics such as security and reliability are becoming increasingly important. Customers may fear that traditional counters are too slow due to inefficiencies of service employees or inescapable interactions. Accordingly, avoiding interactions with the service employee that may be inevitable at the traditional service counter is also seen as a benefit confirming research to date (Dabholkar and Bagozzi, 2002; Meuter et al., 2000) and illustrating that those personal values which can only be provided by service employees become less important. Quite the contrary, people place special value on reducing time, avoiding waiting in line, and increasing the speed of service delivery and therefore, if a new technology meets these requirements, they are more likely to use it (cf. Paper 1).

Second, also in regard of mobile service, the most influential motivations are those supporting "the mobile lifestyle", namely the mobile service's multifunctionality and compatibility. Their clear dominance reveals that customers expect mobile service to fit their lifestyle and to be convenient for managing their daily tasks (cf. Paper 2). Thus, customers expect new digital technologies to be a companion in every life situation. In contrast, the fact that using mobile service may enhance a user's image is not important for the modern user. Image is "the degree to which use of an innovation is perceived to enhance one's image or status in one's social system" (Moore and Benbasat, 1991, p. 195) and in general, individuals are likely to respond to influences within their social systems to establish or maintain a favorable image (Lu et al., 2011). Yet, this dissertation shows that nowadays using mobile service is not related to establishing or enhancing one self's image any more as people have gotten used to these technologies and even more they are taken for granted in the modern daily life (cf. Paper 2).

3) *Threats associated to using new technologies play a less important role for users' behavior (Topic 2).*

When users switch to the relatively new service delivery method of mobile service, they are less afraid of potential disadvantages related to the new technology. Chapter 2.2 reveals that

negative motivations, such as the user's fear of complexity of a new system or privacy risks, which apply when information about a person is used without permission or knowledge, show a minor negative influence on users' behavior. It is particularly important for companies to understand – apart from understanding the reasons why customers switch to a new technology – to also know why people reject them and even more important, how they can be convinced to switch to them. Against this background, in Chapter 2.2 it is found that the risks associated to a new technology, i.e. potential reasons for rejection, are significantly less important for the customers' decision whether to switch or not as compared to the advantages the customers can gain from the switch (cf. Paper 2). Accordingly, customers rather perceive the advantages of the switch and overlook potential disadvantages. This shows that the potential threats associated to using new technologies are not decisive obstacles for customers' switch. In particular, the minor importance of performance risk demonstrates that customers presumably expect the technology to be mature and without functional risks (such as incorrect ticket download). The reason may be a general technology ubiquity in addition with a growing network coverage in today's everyday life. In addition, when users are offered monetary incentives to switch to mobile service despite possibly associated risks, the monetary amount that would be necessary is rather low (cf. Paper 3), elucidating that in a world where people grow up with mobile service becoming an integral part of daily life, even customers who do not use mobile service regularly are not averse from doing it. This underlines that people have gotten used to being confronted with new technologies, which they finally end up adopting and it illustrates their general trust in new technologies.

4) *Users can be classified based on their knowledge exchanging behavior in ESN from a structural as well as from a content perspective. However, the content perspective is indisputable as the mere consideration of the structural characteristics may lead to misinterpretations (Topic 3).*

This dissertation proposes different methodological approaches to classify users of technologies – such as ESN – based on their knowledge exchanging behavior from the structural as well as the content perspective. All approaches classify users based on their amount of sharing and seeking knowledge as one of the following user roles: givers, i.e. users who share disproportional much knowledge as compared to what they acquire, matchers, i.e. users with a comparably balanced amount of sharing and seeking knowledge, and takers, i.e. users who acquire disproportional much knowledge as compared to what they contribute. The applicability of all

approaches is demonstrated using real-world datasets and their results may help companies tremendously to improve their knowledge management – in particular on behalf of new technologies.

First, in Chapter 3.1, two methods based on users' reciprocities in terms of sharing and seeking knowledge in a knowledge base are developed. Thereby, the "Absolute Distance Measure" allows classifying a user regardless of other users, while the "Relative Distance Measure" considers the knowledge exchanging behavior of other users in comparison. The results show that most users behave as takers (cf. Paper 4). However, givers and matchers are characterized by a high activity and connectivity in the network, giving them, from a structural perspective, a central position in the ESN. Having proposed two methods to classify users based on their structural characteristics, this dissertation goes a step further in Chapter 3.2 and proposes a further methodological approach that includes the content perspective. While prior studies mainly focus on the structural perspective (e.g., number of likes, amount of written posts) when identifying user roles, they do not consider the content perspective in sufficient detail (e.g., Beck et al., 2014; Trier and Richter, 2015). Accordingly, a methodological approach is developed which includes this content perspective and considers users' knowledge sharing and seeking in messages using a text analysis approach. The approach consists of three steps, namely "message classification", "identification of users' roles", and "characterization of users' roles". Going beyond this categorization, while the data shows that the majority of messages aims to share knowledge, matchers again are a central element of the network (cf. Paper 5).

The results of all proposed methodological approaches within the scope of this dissertation (cf. Chapters 3.1 and 3.2) are in accordance in illustrating the central role of matchers in ESN. Matchers have the potential to keep these technologies alive due to their high network interconnectedness and activity (such as giving likes, bookmarks etc.). Moreover, they connect various users, spread the information in the network, and thus can transfer knowledge in the most effective way (cf. Papers 4-5). Against this background, organizations are well recommended to identify and address their matchers for an effective knowledge management within the organization. However, the results in Chapter 3.2 illustrate that solely regarding structural characteristics – such as the number of messages written – is not sufficient to identify user roles, which makes an investigation of the contents crucial to reach valid results. When identifying matchers based on their contents exchanged, it is found that they also write most of the messages. Regarding merely the number of messages exchanged, these users would

subsequently be identified as givers (cf. Papers 4-5). Hence, understanding the contents exchanged more in depth is crucial for a reasonable user classification.

4.2 Limitations and Outlook

This dissertation addressed selected aspects of SST and ESN with findings relevant for theory and practice. However, there are also some limitations to this work, which can serve as inspiring starting points for future research and are discussed in the following.

First, within the large research area of digital technologies, this dissertation focuses on two research topics, namely SST and ESN, and contributes to a better understanding of these specific technologies. However, the comprehensive field of digital technologies does not only consist of these two technologies but rather is a complex research field consisting of various technologies and research topics which can be investigated from different perspectives. Digital technologies can be based on hardware, software, and networks and are a fundamental technical, economic, and social challenge of the 21st century, which is why science started calling it "a digital revolution". However, important characteristics are the continuing exponential development of computer technology in many aspects, outrageous large amounts of digital data, and innovation through novel combinations (Brynjolfsson and McAfee, 2015). As a part of this digital revolution, SST and ESN are of increasing prevalence these days and meanwhile play an essential role for people's everyday lives as well as for organizations. This is why they are of special interest for both, research and practice, and are investigated in depth in this dissertation. In addition, the results of this dissertation may hold in a similar form for other digital technologies and the methods proposed may also be applied in related contexts.

Against this backdrop, the methodological approaches for the classification of users and identification of different user roles might, for instance, be adopted and applied to related research fields. Crowdsourcing, cloud computing, microblogs or online social networks are just a few examples thereof. In particular, regarding online social networks, there are potentials to conduct similar analyses as they are characterized by features similar to ESN, yet have larger user communities, which offers great opportunities to investigate the roles of givers, takers, and matchers (cf. Topic 3) more in depth. Examining the roles of different users with respect to their knowledge contribution in messages and posts written in an online social network as well as investigating their structural characteristics on behalf of SNA could help to better understand their knowledge exchanging behavior from both – the structural as well as content per-

spective. The investigation of user roles may also be of particular interest for crowdsourcing platforms, of which one of the most popular examples is Wikipedia. Knowing which participants contribute most to the platform – regarding the structural (e.g., amount of articles) as well as the content perspective (e.g., content of the articles) – enables to address them more targeted. Thus, the roles of givers, takers, and matchers (cf. Topic 3) seems to be promising and could improve the understanding of its users' knowledge exchanging behavior. Moreover, classifying the users based on their contributed contents could reveal those users that really deliver valuable contents. In this context, it can be well assumed that users classified as givers may be especially important and knowing who these users are could help Wikipedia to better engage with them and therefore promote their loyalty. This could for instance also be done on behalf of rewards, such as monetary incentives (cf. Topic 2). Further, the different kinds of motivations identified in this dissertation (utilitarian versus hedonic and positive versus negative) may also well be valid in other contexts and their relative importance can be supposed to vary depending on the environment. To give an example, in the context of checkout-free grocery stores – coming back to the example of "Amazon Go", where an app automatically adds the customers' products to a digital shopping cart – it would be highly interesting if the "just walk out technology" triggers customers' hedonic motivations or if in this case rather negative motivations even gain in importance, for instance due to a possible missing trust in accurate automatic billing or the fear of loss of control as the process takes place "by the way".

Second, all studies have been analyzed based on selected cases, which calls for future research in other contexts. As an example, for the chapters on SST (Subject A) case studies at a retail store and at train stations respectively were conducted to investigate the research objectives. While the investigated SST show typical characteristics as well as user demographics, further validations of the models in other contexts are desirable. The chapters on ESN (Subject B) used real-world datasets of ESN of on the one hand a multinational consulting company and on the other hand the German Armed Forces to validate the applicability of the proposed methodological approaches. In the future, it might be interesting to apply the approaches to other contexts beyond these datasets. For instance, considering user roles in terms of knowledge contribution in ESN of small and medium enterprises (SME) would certainly be a relevant and exciting field of research. Particularly in SME, it is of increasing interest to get insights into knowledge exchange, user roles, and opportunities to motivate employees to participate in knowledge contribution in ESN with the aim to improve the SME's knowledge

management. While big companies are already broadly using ESN for knowledge management, SME still seem to be far behind which is why they represent a very promising research area. The approaches discussed in this dissertation can pose the starting point for future work in this context.

Third, in context of SST (Subject A), this dissertation focuses on selected kinds of SST, namely kiosk SST and mobile service. However, it does not claim to provide an all-encompassing view on SST. The selection of specific kinds of SST is done in a first step to ensure a consistent understanding and to prevent mixing distinct effects that may arise for different kinds of SST. Nevertheless, many other kinds and functions of SST need to be investigated in order to get a profound understanding of this comprehensive research field. In addition, research might further investigate SST in different contexts, for instance with the aim to get insights into which kinds of SST are beneficial for specific usage purposes (e.g., mobile service could be profitable for public transportation while kiosks may be preferred for checkouts in supermarkets) and which functions need to be inherited in different environments. Moreover, the evaluation of the relative importance of users' motivations for SST usage should be extended to demographic differences, such as age or gender, as well as differences between countries. On top of that, it would be interesting to further investigate the cost-benefit relation of SST (based on first insights in Chapter 2.3) and to determine their economic value.

Fourth, in context of ESN (Subject B), users are classified as givers, takers, and matchers based on their number of write and read accesses in a knowledge base (Chapter 3.1) or on their amount of knowledge shared and sought within messages (Chapter 3.2). Obviously, the knowledge exchange in a knowledge base or within messages respectively cannot completely reflect users' knowledge exchanging behavior in the whole ESN. In the future, it would be interesting to investigate the knowledge exchange within other features of ESN. Further, developing a conceptualization covering all opportunities of knowledge exchange in ESN in order to get a comprehensive understanding of the complete knowledge exchanged within ESN would be a promising starting point for future research. Moreover, in Chapter 3.1 content and quality of write and read accesses were not considered which is why further analyses are needed to investigate this aspect in depth. However, complying with this request, Chapter 3.2 already builds upon this first approach in Chapter 3.1 and extends it by additionally addressing the content perspective in such that it investigates the contents of ESN messages for user classifications.

In summary, digital technologies and their users' behavior are a wide and promising research field that is still growing and therefore holds various interesting aspects for further investigation from different perspectives and with different purposes. It remains a highly relevant research field for theory and the insights have a great importance for practice. This dissertation hopefully contributes to a better understanding of SST and ESN as subtopics within the comprehensive research field of digital technologies and stimulates further research on this fascinating topic.

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